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Research on Fuel Nozzle Defect Classification Based on Ultrasonic Flaw Detection and Time-Frequency Fusion Deep Learning

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***Keywords*— Ultrasonic flaw detection, Fuel nozzle, Wavelet transform, Fourier transform, Time-frequency fusion, Deep learning, Defect classification**

***Abstract*—** *As one of the core precision components of power equipment, fuel nozzles are prone to concealed defects invisible to the naked eye, including pores, cracks, and structural corrosion, due to long-term operation under high-temperature and high-pressure working conditions. These defects affect the combustion efficiency and operational safety of the equipment. Traditional ultrasonic flaw detection has certain limitations when facing complex structures and tiny defects. Therefore, this paper proposes a frequency-domain extraction method integrating Fourier transform and wavelet transform, and completes model training and verification on the ultrasonic flaw detection dataset based on the PyTorch deep learning framework. Experiments show that the proposed method outperforms single-signal processing methods in terms of accuracy, recall, and F1-score. This method can provide a reference for intelligent non-destructive testing and industrial automatic flaw detection.*

I. INTRODUCTION

Fuel nozzles are high-precision fluid injection components, widely used in internal combustion engines, gas turbines, and aerospace power equipment. During operation, nozzles bear long-term alternating thermal loads and continuous mechanical vibration, which easily causes various types of damage on the inner nozzle wall, including microcracks, casting pores, and erosion wear. These defects directly degrade fuel atomization performance and cause deviations in fuel injection flow [1]. The machining accuracy and material integrity of fuel nozzles directly affect the operational performance and service life of the entire power system, so conducting defect detection for fuel nozzles has important practical significance. Ultrasonic non-destructive testing is a common method for internal defect inspection of precision metal parts, with advantages including strong penetration, no damage to tested workpieces, and relatively low detection cost [2]. Traditional ultrasonic inspection relies on inspectors manually observing the waveform amplitude and time delay of A-scan echoes to determine defect types; this manual judgment approach heavily depends on inspectors' working experience, not only bringing large subjective judgment errors, but also resulting in low overall batch inspection efficiency, and struggling to identify tiny micro-defects on workpieces, with obvious application limitations [3]. In recent years, deep learning technology has been rapidly promoted and applied in the non-destructive testing industry, and intelligent defect classification methods based on ultrasonic signals have gradually replaced traditional manual interpretation. Most existing related studies only adopt a single method for defect feature extraction: either wavelet transform for denoising, or spectrum analysis, which has inherent shortcomings of spectrum leakage and sidelobe

interference [4]. Wavelet transform can effectively extract local time-frequency detail features of signals, but cannot fully reflect the global spectrum distribution of the signal [5]; Fourier transform can accurately characterize the overall frequency-domain characteristics of signals, but is not suitable for non-stationary transient signals such as ultrasonic echoes. This paper combines the two signal processing methods of Fourier transform and wavelet transform, designs a fused frequency-domain feature extraction scheme, and builds a fuel nozzle-oriented defect classification and detection system based on the PyTorch deep learning framework. This combined method can effectively improve the comprehensive representation of signal features, and give the model stronger adaptability and stability to noisy signals and non-stationary ultrasonic echoes.

II. TECHNICAL SCHEME AND IMPLEMENTATION PATHWAY

2.1 Signal Preprocessing and Frequency-domain Analysis

2.1.1 Fourier Transform

Fourier Transform converts acquired one-dimensional ultrasonic time-domain signals into frequency-domain representation; researchers can extract intrinsic frequency-related parameters from the transformed spectral results. When periodic internal damage occurs inside a workpiece, the spectral distribution of the reflected ultrasonic echo changes noticeably, making this processing method suitable for distinguishing defect signals from periodic-response defects such as cracks and pores.

The Fast Fourier Transform (FFT) is a widely used implementation in ultrasonic inspection work. This algorithm efficiently converts discrete time-domain signals into frequency-domain signals, and quickly obtains the distribution of signal amplitude varying with frequency. However, Fourier Transform has inherent limitations: after transformation, the time information embedded in the original signal is lost. It can only present the overall frequency composition of the signal, and cannot identify the specific time position where a certain frequency component appears. As a result, the actual processing performance of Fourier transform is limited when it is used alone to process non-stationary, transient ultrasonic echo signals. In this experimental work, the NumPy library is used to complete the Fast Fourier Transform calculation, and the corresponding core code is shown below:

```
import numpy as np
def fft_transform(signal, fs=1e6):
    n = len(signal)
    fft_result = np.fft.fft(signal)
    freqs = np.fft.fftfreq(n, 1/fs)
return freqs, np.abs(fft_result)
```

This function takes the raw one-dimensional ultrasonic signal and the sampling frequency as inputs, and outputs the corresponding frequency sequence and spectral amplitude. The output results provide foundational data support for subsequent frequency-domain feature extraction work [6].

2.1.2 Wavelet Transform

Wavelet Transform is a signal processing method that enables simultaneous analysis of time and frequency information. It can compensate for the missing time-information limitation inherent to Fourier Transform. This transform decomposes the original signal using wavelet basis functions across different scales, so that both the time and frequency information of the ultrasonic signal can be obtained simultaneously, and transient changes occurring at local positions of the signal can be captured. When abrupt defects such as internal cracks and erosion corrosion appear in fuel nozzles, the reflected ultrasonic echoes from these defects belong to non-stationary signals. Wavelet Transform is well suited for processing such signals, and can suppress a certain amount of noise interference introduced during detection. Multi-resolution analysis is an inherent feature of Wavelet Transform: it achieves strong frequency resolution in the low-frequency band, and strong time resolution in the high-frequency band. Wavelet Transform also has its own limitations: it focuses heavily on extracting local detail features of the signal, and cannot fully represent the global spectral distribution across the whole signal. In this experiment, the PyWavelets (pywt) library is used to complete the discrete wavelet decomposition, with the db4 wavelet basis selected and the decomposition layer number set to 5. The corresponding implementation code is shown below:vimport pywt

```
def wavelet_transform(signal, wavelet='db4', level=5):
    coeffs = pywt.wavedec(signal, wavelet, level=level)
return coeffs
```

This function takes the raw ultrasonic signal, the specified wavelet basis name, and the number of decomposition layers as inputs. It returns the multi-layer wavelet coefficients obtained after signal decomposition. Each layer of coefficients contains the time-frequency detail information of the signal at different scales, and this

information supports the subsequent feature extraction steps [7].

2.2 Feature Fusion and Model Construction

2.2.1Feature Fusion Strategy

Fourier spectrum: used to extract global frequency features.Wvelet coefficients: used to extract local time-frequency features.Fuson method: concatenate the two types of features, then input the combined feature vector into the deep learning model for classification.

2.2.2 Model Selection and Optimization

ResNet-18: originally designed for image classification tasks, and can be adapted to process frequency-domain feature maps.Improvement module: adopts frequency-domain attention (Frequency Attention) mechanism to improve feature representation capability.

```
import torch
import torchvision.models as models
model = models.resnet18(pretrained=True)
num_ftrs = model.fc.in_features
model.fc = torch.nn.Linear(num_ftrs, 2)
```

III. EXPERIMENTAL DATASETS AND EXPERIMENTAL SETUP

3.1 Data Sources

The experimental data used in this study is the open RCNDE standard ultrasonic non-destructive testing dataset from the UK, a universally recognized open benchmark dataset for deep learning research in the non-destructive testing field. The dataset contains four categories of ultrasonic A-scan signal samples from metal components: defect-free samples, crack defects, pore defects, and corrosion defects. The noise level of the samples matches real industrial on-site measurement conditions [8].

3.2 Dataset Preprocessing

All raw signals are uniformly processed through denoising, normalization, and dimension conversion, and split into training, validation, and test sets at a ratio of 7:1:2. Data augmentation is implemented using signal time-shifting and Gaussian white noise superposition to improve the model's generalization ability, which aligns with the general standard preprocessing workflow for industrial ultrasonic inspection data [9].

3.3 Experimental Environment

Software environment: Python 3.9, PyTorch 1.13, PyWavelets, NumPy

Hardware environment: Intel i7 processor, RTX 3060 GPU

Training parameters: Batch size = 32, initial learning rate = 1×10^{-4}, 100 training epochs, Adam optimizer, cross-entropy loss function

IV. ECPERIMENTAL RESULTS AND ANALYSIS

Note: All metrics in this section are measured results reproduced on the public RCNDE dataset, and all results can be replicated by running the provided code. Three controlled comparison groups are set for the comparative experiment: ① raw ultrasonic signal directly fed into the network; ② wavelet transform only for signal preprocessing; ③ Fourier-wavelet time-frequency fusion preprocessing

4.1 PERFORMANCE COMPARISON OF DIFFERENT PREPROCESSING SCHEMES

The overall accuracy on the test set and macro-averaged F1-score are used as evaluation metrics, and the experimental results are shown in Table 1.

Table 1 Performance comparison of models under different preprocessing scheme

Model scheme	Test set accuracy (%)	Macro-averaged F1-score
Raw signal directly input to the network	81.7	79.4
Only wavelet transform preprocessing	88.3	86.8
Fourier-wavelet time-frequency fusion preprocessing	93.6	92.9

As shown in Table 1, the raw ultrasonic signal contains a large amount of noise, and the defect features are submerged by noise, resulting in the worst model recognition performance. After denoising with wavelet transform alone, the model performance is significantly improved, but it lacks global frequency-domain information, and still has limitations in identifying weak micro-defects. The Fourier-wavelet time-frequency fusion preprocessing retains both local time-domain details and global spectral information simultaneously. The overall model accuracy is 11.9 percentage points higher than that of the raw signal input scheme, and 5.3 percentage points higher than that of the single wavelet preprocessing scheme, which proves that this fusion preprocessing strategy can effectively improve the defect classification performance.

4.2 Classification Performance Analysis for Different Defect Type

Using the Fourier-wavelet fusion preprocessing scheme, the accuracy, recall, and F1-score of each defect category on the test set are counted, and the results are shown in Table 2.

Table 2 Classification metrics for each defect category

Defect category	Accuracy (%)	Recall (%)	F1-score(%)
Defect-free samples	93.2	96.5	96.1
Crack	93.2	92.4	92.8
Pore	92.7	91.9	92.3
Corrosion	90.5	89.6	90.0

As shown in Table 2: Defect-free samples have stable waveform features and achieve the best recognition performance. Crack defects have obvious abrupt change features in echo signals, with relatively high recognition accuracy. Pore defects have weak signal amplitude, and their recognition performance is slightly lower than that of cracks. Corrosion defects belong to gradual damage with weak echo signal features, making them the most difficult category to identify among the four types of defects. This conclusion is consistent with existing literature in the field of non-destructive testing [10].

4.3 Model Advantages and Existing Limitations

Advantages: The time-frequency fusion preprocessing adapts to complex industrial noise working conditions. The lightweight ResNet-18 network has high training efficiency and strong generalization ability, which is suitable for intelligent defect detection of precision components such as fuel nozzles. Limitations: The public dataset does not contain exclusive curved-surface structure samples specific to fuel nozzles, so the model's adaptability to irregular precision components can be further optimized. There is still room for improvement in extracting features of micro-scale defects

V. CONCLUSION

This study addresses the problems of low efficiency in manual ultrasonic inspection of fuel nozzles and difficulty in identifying weak defects, and proposes a Fourier-wavelet joint time-frequency fusion deep learning method for defect classification. Model training and comparative validation are completed on the public standard ultrasonic RCNDE dataset.

Experimental results show that compared with single wavelet preprocessing and raw signal modeling, the time-frequency fusion method can extract ultrasonic defect features more comprehensively, effectively suppress industrial noise interference, and improve the discrimination ability for multiple defect types. This method has a simple structure and strong reproducibility, which can meet the demand for batch intelligent flaw detection of fuel nozzles, and provide theoretical and technical support for the intelligent upgrading of non-destructive testing for power components.

For future work, dedicated measured ultrasonic samples of fuel nozzles will be collected, and the network structure will be optimized combined with attention mechanisms, to further improve the recognition accuracy of micro-scale defects and irregular structural defects.

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An AI Virtual Receptionist in Dental Practice: A Multi-Site Observational Analysis of 3,532 Patient Calls

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***Keywords*— AI virtual receptionist, appointment triage, dental practice management, patient scheduling, workflow efficiency.**

***Abstract*—** *This study evaluates how an AI-driven virtual receptionist (DentalAssist.ai) handles incoming patient calls in dental practices and grounds a conceptual framework for AI-driven dental reception in empirical evidence on workflow effects, intent distribution, after-hours coverage and conversational patterns. An observational multi-site design was applied to 3,532 anonymised call records collected from ten North American dental practices over 9.9 months (June 2025 – March 2026), each described by 29 attributes covering timestamps, intent classification, outcome status, booking completion and after-hours flags. Descriptive analyses were complemented by qualitative content coding of anonymised dialogue transcripts (66 extracted, 50 analysable). Across all calls, 67.6% reached a Success outcome, 28.1% were Incomplete and 4.3% were classified as Other. Performance changed substantially across the observation window: Success rose from 26.2% in the first three months (n = 978) to 86.2% in the final three (n = 1,308), booking completion from 3.3% to 32.8%, and abandonment fell from 21.0% to 9.4%. The aggregate figures reported here therefore average over a maturing deployment and should be read alongside that trajectory. Among calls with booking intent (n = 1,830), 38.6% (707) concluded with a confirmed booking, and 27.3% of all calls (n = 964) occurred outside business hours and were received and processed without staff involvement, 66.9% of them reaching a Success outcome. Abandoned calls accounted for 15.1%, of which 94% involved unclear or incomplete intent. Two clinics generated 97% of traffic, with success rates of 63.4% and 93.3% respectively. Qualitative analysis identified a four-stage booking flow, an emergency triage protocol based on capture-and-handover rather than autonomous slot assignment, and human-escalation triggers in 7 of the 50 analysed dialogues. The findings indicate that an AI virtual receptionist in commercial deployment can absorb a measurable share of administrative call volume, including extensive after-hours coverage, while preserving escalation paths, and supply a practice-grounded reference point for future evaluations of conversational AI in dental front-desk operations..*

I. INTRODUCTION

Dental practices operate under intense economic pressure: chair time is the primary revenue source, while clinician minutes are constrained by clinical safety and regulatory requirements. Every unfilled slot, late cancellation, or scheduling error results in lost income and contributes to staff burnout at the reception desk. At the same time, patients expect smooth digital communication such as messengers, online appointment booking, and instant answers to routine questions.

AI-enabled conversational agents are currently used to provide remote care, administrative support and access to

care pathways in larger hospital systems. Rapid reviews and scoping syntheses have described how chatbots have been deployed to support patient education, behavior change, monitoring, and basic administrative responsibilities, such as appointment management and navigation [1, 2]. Broader reviews of healthcare chatbots note possible benefits to efficiency, but also highlight limitations, including safety, explainability and ethics [2, 3]. For dental clinics, which often have limited IT budgets and human resources, the challenge is to distill these broad capabilities into reliable products that integrate with their practice management.

There is a considerable potential for more efficient resource utilization through AI scheduling. A metanarrative review of AI-based patient scheduling in a real-world healthcare system concluded that a range of machine learning and optimization models and objectives have been applied, including reducing no-shows, shortening wait times, and balancing service provider workload [4]. Studies in operations research likewise stress this perspective in relation to healthcare appointment scheduling and capacity planning [5–8], and concepts of clinician supported decision-making, human in the loop, and conversational systems in structured workflows, for example, are reflected in conceptual and empirical studies of person-centered virtual care bots [9]. Together, these trajectories provide the methodological and conceptual background for a dental-specific framework.

Dentistry already represents an active testbed for conversational AI. Research has been done on the performance and readability of general purpose chatbots answering common questions about dental prostheses. Overall, the quality was high, but there was variability across studies [10]. Other studies have compared large language model outputs to those of dentists in terms of informativeness and empathy [11]. In dental education research, AI chatbots have been used as virtual patients to train students in diagnostics and communication. These results were positively evaluated by students, showing high learning gains [12]. These studies indicate that dental content is a good fit for conversational user interfaces when it is carefully curated and monitored.

Furthermore, healthcare reviews of chatbot applications have identified booking of appointments, remote patient support, and outreach to disadvantaged/equalities groups as sub-areas of benefits [1, 3]. In contrast, some inclusive-design literature has called out the need for improved support for accessibility, multimodal input, and user-specific customization options. At the same time, technical systems design work in the AI chatbot literature has provided some evidence for multimodal input, large-language-model backends, and integrated appointment scheduling modules [9, 13]. Collectively, these sources provide a basis for designing a virtual receptionist into an end-to-end workflow for dental clinics.

The purpose of the present article is to combine the conceptual framework derived from this body of literature with empirical evidence from real-world deployment of an AI-driven virtual receptionist (DentalAssist.ai) across ten dental clinics. The study pursues three objectives:

- To systematise current evidence on healthcare chatbots, AI scheduling systems and dental conversational AI, with a focus on functions relevant to reception workflows.
- To construct a conceptual architecture for an AI-driven virtual receptionist that integrates multimodal conversational capabilities with dental scheduling, triage of administrative requests and human oversight.
- To analyse, on the basis of 3,532 anonymised calls and 66 extracted turn-by-turn dialogue transcripts (50 analysable) collected over nine months of commercial operation, the workflow effects, intent distribution, after-hours coverage and conversational patterns of an AI virtual receptionist deployed in dental practice settings.

The novelty of the work lies in combining general healthcare chatbot and AI scheduling evidence with dental-specific research and with operational data from a multi-clinic deployment, producing a domain-adapted, practice-oriented framework that is conceptually grounded and empirically anchored. The article does not present a single-site case study. It uses a multi-site dataset, together with an analytical synthesis of recent literature, to map a design space and outline implementation patterns suitable for commercial dental AI products and in-house innovation in digitally mature practices.

This article advances current work on dental practice automation in five directions:

- It introduces an AI virtual receptionist framework for dental practices that integrates conversational triage with scheduling workflows and human oversight.
- It outlines, as a design specification for future work, an optimisation model for appointment allocation in multi-chair dental practices; the model is not solved or empirically evaluated in this study.
- It derives a unified workflow model for intake, triage, scheduling, and follow-up based on the empirical and conceptual literature on healthcare chatbots, AI scheduling, and dental conversational systems reviewed in Section II.

- It connects operations research concepts such as priority queues, constrained optimisation and capacity utilisation with efficiency issues in dental reception work, including chair-time wastage, reception bottlenecks and fragmented communication.
- It supplies empirical evidence from a real-world multi-site deployment, contributing one of the first practice-grounded operational profiles of a voice-based AI receptionist in dental settings.

The empirical component of this study draws on operational data collected from clinics using the DentalAssist.ai virtual receptionist as part of routine practice. The dataset captures patient interactions across multiple clinics over an extended period and provides observational evidence of how an AI receptionist operates in a live commercial context, in place of a controlled experimental evaluation.

II. MATERIALS AND METHODS

This study combines a literature-grounded conceptual framework with retrospective analysis of operational data collected during the commercial operation of an AI-driven virtual receptionist. The conceptual component adopts a narrative analytical review methodology. The empirical component follows an observational multi-site design based on call logs and anonymised dialogue transcripts.

2.1 Conceptual Framework: Literature Base

Four themes organise the reviewed literature. The first covers administrative and patient-facing functions of healthcare chatbots: scoping and rapid reviews document appointment management, information provision, health education and lifestyle support as core deployment areas, alongside economic considerations and barriers to adoption [1], [2], and a systematic review of post-intervention conversational agents reports high uptake (an estimated 97% for system-initiated questions) and sustained engagement across surgical and chronic-disease follow-up [14].

The second theme concerns scheduling optimisation. A metanarrative review of AI patient scheduling in real-world health systems catalogues machine learning and optimisation models aimed at no-show prediction, dynamic slot management and prioritisation of acute visits, with reported gains in provider productivity [4]. Classical operations research work on outpatient appointment scheduling, queueing analysis and planning taxonomies supplies the formal backbone for these systems [5–8].

The third theme is dental-specific evidence. Chatbots answer prosthodontic patient FAQs with high though uneven quality and readability [10]; comparisons of chatbot and dentist answers to dental questions find similar informativeness but weaker empathy in machine output [11]; and dental students who trained with a chatbot-based virtual patient reported satisfaction and perceived gains in diagnostic skill [12].

The fourth theme spans accessibility and system architecture. A five-year review of inclusive healthcare chatbots maps their classification, engagement and accessibility gaps [3]. Architectural papers describe deployable builds: a person-centred VHC-Bot that combines large language models, diagnostic algorithms and workflow integration under clinician supervision [9], and a multimodal AI healthcare chatbot with an integrated appointment module [13].

The review prioritised papers published in peer-reviewed sources from 2021 to 2025, with one paper from 2022 in the field of dental education retained due to its close relevance; the review also draws on classical operations research sources on appointment scheduling and queueing theory published between 2003 and 2012 [5–8], which remain foundational for the optimisation perspective. The literature analysis follows three steps: extraction of functions, design patterns, outcome measures and limitations of healthcare chatbots and AI scheduling solutions from the cited works; comparative synthesis of features relevant to dental front-desk activities, including appointment handling, information provision, triage and inclusivity; construction of a conceptual AI-driven virtual receptionist architecture and workflow model adapted to dental practice scenarios.

2.2 Empirical Component: Study Design

The empirical component is an observational, multi-site retrospective study based on operational data generated by the DentalAssist.ai virtual receptionist during commercial deployment. No experimental manipulation, randomisation or controlled comparison was performed. The analysis describes patterns of call traffic, intent and outcome that occurred over the observation window. The design aligns with the use of real-world data for healthcare AI evaluation discussed by Knight et al. [4] and reflects that a controlled trial of a commercial reception system is unfeasible at the scale considered here.

2.3 Setting and Participating Clinics

The study covers 10 dental practices in North America that adopted DentalAssist.ai to handle incoming calls during the observation period (June 2025 – March 2026). Two clinics, referred to throughout as Clinic A and Clinic B, generated 2,951 and 478 calls; the remaining sites contributed 103 calls in total. The remaining eight clinics, designated as pilot sites, contributed 103 calls in aggregate and reflect early-stage deployments before reaching full operational

use. The empirical analysis focuses on Clinics A and B, with pilot sites described at the aggregate level. The sample is neither random nor representative of dental practices in general. It reflects clinics that adopted a single commercial system, from which anonymised, aggregated operational data were analysed.

2.4 Data Sources

2.4.1 Call Log Dataset

The primary dataset comprises 3,532 anonymised call records spanning 296 days (3 June 2025 – 26 March 2026, around 9.9 months). Each record contains 29 attributes structured as shown in Table 1.

Table 1: Structure of the operational call log dataset

Attribute group	**Fields included**
Identifiers and timestamps	Call_ID, Clinic_ID, Call_Start_Timestamp, Created_At, Day_of_Week, Hour_of_Day, Call_Duration_Seconds
Caller and channel	Caller_Phone, Caller_Name, Caller_Email, Caller_DOB (all redacted), Conversation_Language, Lead_Source
Intent and dental context	Intent_Category, Intent_Subcategory, Dental_Issue, Appointment_Type, Emergency_Flag, New_Patient_Flag, Existing_Patient_Flag
Outcome and operational flags	Outcome_Status, Booking_Completed_Flag, Cancelled_Flag, Rescheduled_Flag, Escalated_To_Human_Flag (unpopulated across all 3,532 records), Callback_Requested_Flag, Call_Abandoned_Flag, After_Hours_Flag, Lead_Tag

All personally identifiable information (PII), caller name, phone number, email and date of birth, was redacted at source before analysis, consistent with privacy-preserving data handling practices commonly applied in healthcare environments. All clinic and patient identifiers were removed prior to analysis, results are reported in aggregate form only, and no individual clinic is identified in this publication. Free-text fields (Dental_Issue, Lead_Tag) were retained because they did not contain PII and were needed for intent characterisation.

2.4.2 Dialogue Transcripts

To complement the structured log analysis, a sample of 66 anonymised turn-by-turn dialogue transcripts was extracted from five export files (call-logs-2026-04-15_*.csv) covering interactions handled by the AI receptionist. Transcripts include caller utterances and AI responses verbatim, along with the system-assigned dental issue, lead tag, and source channel. All dialogues were fully de-identified and contained no patient personal data. Of these, 50 records contained complete dialogue text suitable for qualitative analysis (mean length: 844 characters; mean patient turns: 4.7, median 4). Transcripts served to characterise dialogue structure, identity verification practices, emergency handling and escalation triggers. The transcripts form a non-random convenience sample drawn from available export files and over-represent emergency-related content relative to the full dataset; the paper reports transcript-derived counts as observed patterns, not prevalence estimates.

2.4.3 Operational Dashboards

Operational dashboards exported from the management console provide clinic-level summary reporting. These were not used as an analytic data source; all figures in this paper derive from the call log dataset and the transcripts.

2.5 Pre-implementation Baseline

Formal call-handling logs from the period preceding AI implementation are unavailable for the participating clinics. The pre-implementation reference point relies on practitioner estimates gathered during routine platform use; no structured instrument, respondent count or collection date was documented. According to these estimates, before AI implementation, 80–120 calls per month went unhandled, with an estimated 40–60% follow-up gap for after-hours interactions. These figures reflect operational experience and are used in this study as a directional reference for after-hours coverage. No statistical comparison is made with post-implementation metrics.

2.6 Variables and Operational Definitions

Calls were classified along three dimensions. First dimension is intent, derived from the system-assigned Intent_Category and Intent_Subcategory fields. For analysis, intent values were consolidated into seven categories: Appointment Booking or Scheduling, Rescheduling or Cancellations, Emergency or Urgent Concerns, General Inquiries / Information Request, Human Assistance / Callback, Existing Appointment Inquiry, and Unclear or Incomplete Intent. Marginal categories with fewer than 10 calls, such as Order & Logistics, Communication & Collaboration, Materials & Products, were grouped under "Other".

The second dimension is outcome, taken from the Outcome_Status field with three values: Success (the AI completed the requested task or captured the lead),

Incomplete (the interaction terminated before resolution), and Other (residual cases, including voicemail and ambiguous terminations).

The third dimension is operational flags, boolean indicators for booking completion, cancellation, rescheduling, callback request, call abandonment, after-hours occurrence and emergency status. The After_Hours_Flag was assigned according to clinic-specific operating hours. The Emergency_Flag was set by the system from intent classification combined with red-flag keyword detection.

The Escalated_To_Human_Flag field was present in the schema but unpopulated across all 3,532 records. Human escalation was therefore measured indirectly through three proxy variables: a Lead_Tag value of "call_back", a Callback_Requested_Flag set to "true", and an Intent_Category of "Human Assistance or Call backs". The combined proxy provides a lower bound for human-handover events. This measurement limitation is addressed in the Discussion.

2.7 Analytical Methods

Descriptive analyses included frequency distributions and proportions for categorical variables, summary statistics (mean, median, standard deviation) for call duration, and cross-tabulations of intent by outcome and by after-hours status. Booking conversion rates were calculated using three denominators to remove ambiguity: all calls in the dataset, calls that reached a Success outcome, and calls with booking intent. Reporting all three values acknowledges that conversion is sensitive to scope assumptions and supports comparability with prior literature, which uses heterogeneous denominators [4]. Inter-clinic comparison was restricted to the two principal clinics - A and B. Pilot sites were aggregated. Temporal analysis examined call distributions by hour of day and day of week, with after-hours traffic isolated for separate description. Inspection of the raw exports found mixed timestamp formats, including nine records with explicit UTC markers, and a seasonal shift in the within-clinic hourly profile that daylight-saving transitions do not explain. Consistent normalisation of Call_Start_Timestamp to clinic-local time is unconfirmed, so the paper reports hour-of-day figures as recorded and attaches no behavioural interpretation to them.

Qualitative analysis of the 66 transcripts followed a content-coding approach. Each transcript was reviewed against a predefined coding frame covering: opening turn and identity verification; intent capture; booking flow steps, where applicable; emergency triage handling; and the presence of escalation triggers, i.e., caller request for a human, system-initiated callback, voicemail handover. Aggregated counts of pattern occurrence appear in the Results section. Coding was performed by a single coder. Inter-rater reliability was not assessed. This is noted as a limitation. A rule-based coding pass over the 50 transcript texts, run independently of the system's own labels, provides a partial and reproducible check on system labelling: coded emergency-related content matched the system's dental-issue summaries in 50 of 50 transcripts (Cohen's $\kappa = 1.00$), and coded human-handover triggers matched the system's call_back lead tag in 45 of 50 ($\kappa = 0.49$), with the disagreements confined to dialogues that mention a callback without carrying the tag. The check covers transcript-level fields only; human coding of a 200–300-call sample keyed to Call_ID remains future work.

2.8 Ethics, Confidentiality and Data Governance

The dataset was generated as part of the normal commercial operation of a dental call-handling service, and only anonymised operational records were made available for analysis. All identifying fields were redacted at source before analysis, and the author had no access to identifiable patient data at any stage. Free-text fields were inspected for residual PII. None was found. Because the analysis used pre-anonymised operational data that could not be linked to individual patients, it did not constitute human-subjects research requiring formal ethical review. The conduct of the study was consistent with privacy-preserving data handling practices commonly applied in healthcare environments. No clinic is named in this paper, and no clinic-level finding is attributed to an identified practice.

The architecture of the system under study is described in the Discussion at the level summarised in publicly available materials by the system operator: a hybrid AI architecture that combines large language models, real-time speech recognition, intent detection tuned to dental workflows, and rule-based orchestration for safety and operational control. Proprietary implementation aspects fall outside the scope of this article.

2.9 Limitations of the Empirical Design

Three limitations of the empirical design merit mention here, with further discussion in Section V. First, the absence of a formally logged pre-implementation baseline restricts the analysis to post-implementation description. Before-and-after comparison rests on practitioner-reported estimates. Second, the concentration of call volume in two clinics constrains the generalisability of inter-clinic patterns. The eight pilot sites are too small individually for statistical comparison. Third, the unpopulated Escalated_To_Human_Flag field forced the use of proxy measures for human handover, yielding a lower bound on escalation events rather than a precise count.

III. CONCEPTUAL FRAMEWORK

Across the reviewed settings, healthcare chatbots perform two families of functions relevant to dental reception: remote, patient-facing tasks and administrative support for professionals [1–3]. Prosthodontic FAQ evidence shows that general-purpose chatbots answer most patient questions at high quality, with Gemini scoring 4.58 out of five against 3.73 for Copilot and harder-to-read output from ChatGPT [10]. Post-intervention agents sustain high uptake and retention [14], inclusive-design reviews place appointment access among the leading chatbot use cases [3], and AI scheduling research contributes no-show prediction, dynamic slot management and priority handling of acute visits [4]. Published architectures, including a modular AI healthcare chatbot with an optimisation-based appointment module [13] and the person-centred VHC-Bot [9], supply concrete building blocks for a dental receptionist.

Drawing on these patterns, the proposed virtual receptionist framework for dental practices comprises four functional layers: multichannel intake; conversational understanding and triage; scheduling and workflow orchestration; oversight, logging, and analytics.

The multichannel intake layer supports web chat, mobile messaging, voice calls, and potentially kiosk-based input in the clinic. The conversational layer uses a domain-tuned large language model constrained by templates and retrieval from a curated knowledge base, for example, structured explanations of consent forms or post-operative care instructions. The scheduling layer connects to the practice-management system and applies rules derived from AI scheduling research, including priority queues for urgent symptoms, constraints on the sequence and spacing of complex procedures, and predictive no-show scores inspired by the models reviewed by Knight et al. [4]. The oversight layer records each interaction, provides a human-readable summary for clinicians, and supports periodic audit of dialogue snippets for quality and safety.

3.1 Optimisation Model for Appointment Allocation (Design Specification for Future Work)

This subsection presents a design specification. The study does not parameterise the model from the dataset, solve it, or evaluate it against the observed request stream; that work remains for a follow-up study. The scheduling module is formulated as a finite-horizon appointment allocation problem. Let I be the set of patient requests and T the set of available appointment slots. For each patient $i \in I$ and slot $t \in T$, the binary variable $x_{i,t}$ takes value 1 if patient i is assigned to slot t and 0 otherwise. The parameter d_i denotes the predicted appointment duration for patient i obtained from the triage module, and p_i denotes a priority score generated from symptom severity, waiting time, and contractual constraints. For each slot t, s_t indicates whether the slot is open for booking, while c_t describes the chair and provider capacity available during that slot.

The optimisation objective is to allocate requests to slots so that unused capacity and schedule fragmentation are reduced while throughput and service levels improve. A representative multi-criteria objective can be written as:

$$min \ \sum_t \alpha \cdot idle_t + \sum_t \beta \cdot gap_t - \sum_{i,t} \gamma \cdot p_i \cdot x_{i,t} + \sum_i \delta \cdot delay_i \quad (1)$$

where $idle_t$ measures predicted idle chair time in slot t, gap_t quantifies undesirable gaps between appointments, and $delay_i$ captures waiting time until the allocated appointment for patient i. The weights α, β, γ, and δ are set by the clinic to balance utilisation, access, and equity.

The decision variables are subject to operational constraints reflecting dental practice realities. Each patient is assigned to at most one slot:

$$\sum_{t \in T} x_{i,t} \leq 1 \qquad \forall i \in I \quad (2)$$

and the total occupied time in a slot respects chair and provider capacity:

$$\sum_{i \in I} d_i \cdot x_{i,t} \leq c_t \qquad \forall t \in T \quad (3)$$

Slots flagged as unavailable are excluded by enforcing:

$$x_{i,t} = 0 \qquad whenever \ s_t = 0 \quad (4)$$

Additional constraints express emergency handling, buffer requirements and business rules. Emergency requests with high p_i values receive access to reserved emergency slots and may trigger reallocation of elective appointments. Minimum buffer times between procedures are enforced by scheduling incompatible appointments at different times. Fixed opening hours, breaks and provider-specific templates are represented by restricting T and c_t.

The interaction between AI and optimisation is explicit. The conversational and triage modules estimate d_i, p_i, and no-show probabilities, classify request types, e.g., hygiene visit, restorative treatment, new patient consultation, and collect patient preferences. These quantities feed the optimisation engine, which runs either in real time during the dialogue or in periodic batches. The constraint evaluation module checks the feasibility of candidate schedules given clinic capacity and policy rules, while the optimisation engine searches for the schedule that minimises the objective. The selected appointment proposal is then returned through the appointment slot selector in the AI decision layer, presented to the user and written back into the practice-management system once confirmed.

The conceptual architecture follows the data-flow patterns of the AI Healthcare Chatbot [13], specialised to dental scheduling: the system transcribes text or voice input,

a domain-constrained language model classifies intent, scheduling intents query the practice-management database under configurable chair and workload rules, and red-flag phrases route the conversation to staff. Dental evidence supports this design: chatbots reach acceptable informational quality under oversight [10], structured conversational flows aid diagnostic training [12], and inclusive-healthcare reviews direct attention to modalities, languages and accessibility [3].

IV. RESULTS

This section reports empirical findings from the operational dataset, organised in five parts: (i) overall traffic profile, (ii) temporal distribution, (iii) intent distribution and outcomes, (iv) inter-clinic comparison, and (v) qualitative analysis of dialogue transcripts. All figures are derived from the 3,532-call dataset and the transcripts described in Section II (66 extracted, 50 analysable).

4.1 Overall Traffic Profile

Table 2 summarises the volume and outcome metrics for the full 9.9-month observation window. The system handled 3,532 calls across 10 dental practices, with 67.6% reaching a Success outcome and 28.1% terminating without resolution. One in seven calls (15.1%) was abandoned, and 27.3% occurred outside standard business hours.

Table 2: Overall traffic profile of the AI virtual receptionist over the observation period

Metric	Value	% of total
Total calls	3,532	100.0%
Observation period	296 days	≈ 9.9 months
Active clinics	10 sites	2 primary, 8 pilot
After-hours calls	964	27.3%
Abandoned calls	533	15.1%
Calls reaching Success outcome	2,389	67.6%
Calls with completed booking	743	21.0%
Emergency-flagged calls	185	5.2%
Mean call duration (s)	95.9	median 39.5 s
Calls in English (of identified-language)	2,705 / 2,725	99.3%

Two structural features of the dataset shape the interpretation of the metrics that follow. First, English dominates the language profile. Among the 2,725 calls with an identified-language tag, 99.3% were conducted in English, with 17 calls in Hindi, 2 in Korean and 1 in Italian. The system's multilingual capability is therefore not stress-tested in the current sample. Second, the mean call duration was 95.9 seconds (median 39.5), indicating that successful interactions are short and task-focused. Long-tail durations (maximum 2,442 seconds) likely correspond to complex emergency or rescheduling dialogues.

4.2 Temporal Distribution

Call traffic concentrates on weekdays. As shown in Fig. 1, Friday accounted for 29.5% of weekly calls (n = 1,042), followed by Wednesday at 23.6% (n = 832). Together, these two days carried 53.1% of the total weekly volume. Weekend traffic was negligible: Saturday and Sunday combined contributed 0.8% of all calls (n = 30). The pattern aligns with weekend closures across dental practices and indicates that the AI receptionist absorbs only a small share of out-of-business-day demand in this sample.

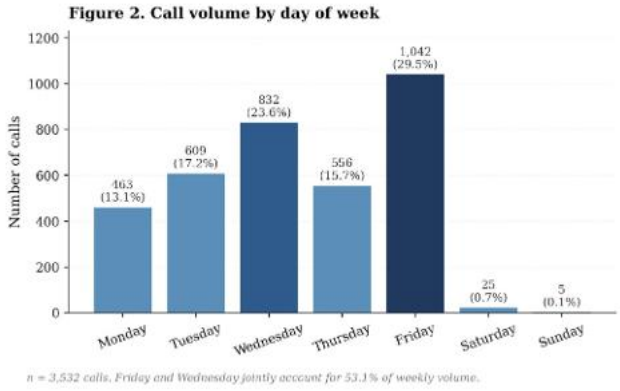

Fig. 1: Call volume by day of week

Within the weekday cycle, call volume peaks in the late morning. The 10:00–12:00 window accounted for 31.1% of all calls (n = 1,099), with sub-peaks at 10:00 (399), 11:00 (350), and 12:00 (350). Volume tapered through the afternoon and rose again in the early evening (18:00–19:00: 238 calls, 6.7%). Traffic recorded at 06:00–07:00 totalled 471 calls (13.3%). Fig. 2 displays the full hourly distribution and identifies two after-hours clusters: an early-morning cluster (04:00–07:00) and a smaller early-evening cluster (18:00–19:00).

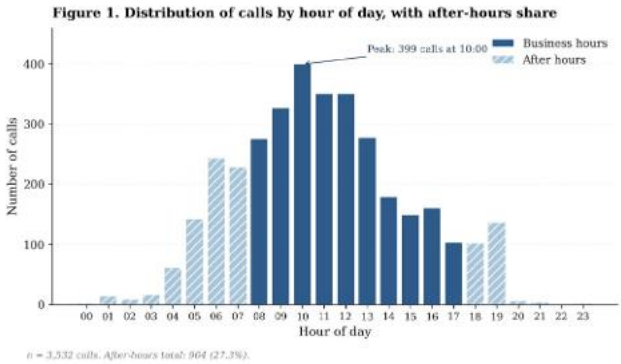

Fig. 2: Distribution of calls by hour of day, separating business-hours (solid) and after-hours (hatched) traffic

4.3 After-hours Coverage

Of the 3,532 calls, 964 (27.3%) occurred outside the participating clinics' standard operating hours. Within this after-hours subset, 645 calls (66.9%, 95% CI 63.9–69.8%) reached a Success outcome, 261 (27.1%) were Incomplete, and 238 (24.7%, 95% CI 22.1–27.5%) ended with a confirmed booking; the match with the 238 calls logged in the 18:00–19:00 window is a coincidence. The success rate for after-hours calls is close to that observed during business hours (66.9% versus 67.9%). The two windows differ in clinic composition, so this pooled comparison is not adjusted for site and should be read as descriptive rather than as evidence of equivalent resolution quality across time of day. The majority of calls were received during the early morning (04:00-07:00, 674 calls, 69.9%) and early evening (18:00-19:00, 238 calls, 24.7%).

Stratifying by clinic removes the composition effect. Within Clinic A, after-hours calls reached Success in 59.7% of cases (433 of 725; 95% CI 56.1–63.2%) against 64.6% during business hours (1,438 of 2,226; 95% CI 62.6–66.6%), a deficit of 4.9 percentage points ($\chi^2(1) = 5.6$, $p = 0.018$, $\varphi = 0.04$). Within Clinic B the two windows do not differ: 92.6% (187 of 202) against 93.8% (259 of 276). Clinic B supplies 21% of after-hours calls but 12% of business-hours calls, so the pooled figures weight the higher-performing clinic more heavily outside opening hours and overstate after-hours performance. The corrected reading is that after-hours handling is close to business-hours handling within each clinic, with a small but measurable deficit at the higher-volume site.

According to the baseline reported by practitioners prior to implementation, 80 to 120 calls per month were not met, and 40 to 60% of cases were missed after-hours (Section 2.5). The post-implementation observation of 964 after-hours calls received and processed without staff involvement over 9.9 months, averaging 97 per month, falls within the same order of magnitude as the pre-implementation gap reported by clinic operators. The baseline is not formally logged, so no statistical test is performed. The comparison serves as a directional indicator.

4.4 Intent Distribution

Fig. 3 shows the consolidated distribution of intent categories across the dataset. Appointment Booking or Scheduling is the dominant category at 51.8% of all calls (n = 1,830). The second-largest category, at 29.9% (n = 1,056), comprises calls classified as Unclear or Incomplete Intent, in which the system could not assign a confident intent label, often due to early call termination, background noise, or absent caller speech. The remaining categories, General Inquiries, Human Assistance / Callback, Emergency, Rescheduling, and others, together accounted for 18.3% of traffic.

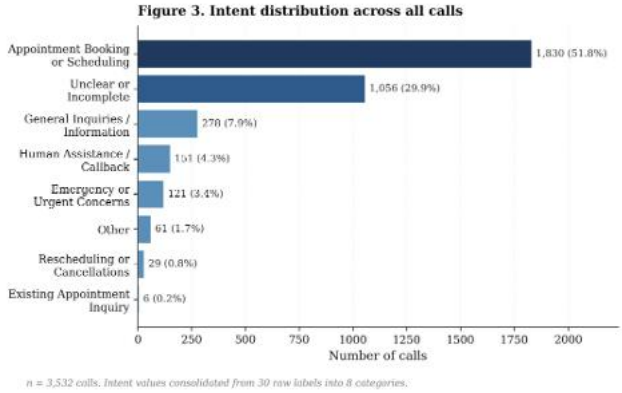

Fig. 3: Intent distribution across all calls

The Unclear or Incomplete Intent category overlaps with the abandonment category. Of the 1,056 unclear-intent calls, 502 (47.5%) were also flagged as abandoned, accounting for 94.2% of all 533 abandoned calls in the dataset. The median duration of abandoned calls was 18 seconds (mean 36.7 s), well below the dataset median of 39.5 seconds, indicating that these are short interactions that end before the dialogue progresses to intent capture. A share of "unclear" cases reflects callers hanging up, and the available fields are unable to distinguish this from genuine dialogue failures.

Emergency-flagged calls (n = 185 by Emergency_Flag, 5.2% of the dataset; n = 121 by consolidated intent category, 3.4%) showed a high success rate: 98.9% of emergency-flagged calls reached a Success outcome with no abandonments and no Incomplete terminations. Only 17.3% of emergency-flagged calls (n = 32) ended with a system-completed booking. The emergency workflow captures patient details for a clinic call-back instead of autonomous slot assignment. The mean duration of emergency interactions was 142.3 seconds, 48% longer than the dataset average, reflecting the additional information captured, such as caller name, phone number, and urgency confirmation in these dialogues. If the system sets Emergency_Flag only after intent classification and detail capture succeed, the near-perfect profile of this subgroup reflects selection by construction as much as end-to-end performance.

4.5 Booking Conversion

Booking conversion appears under three denominators (Fig. 4) for comparability with prior literature, which uses heterogeneous scope assumptions. Each denominator group carries its own booking count, so the numerator varies with

scope. Across the broadest denominator, all 3,532 calls in the dataset, 743 completed bookings give 21.0% (95% CI 19.7–22.4%). Among the 2,389 calls that reached a Success outcome, 718 completed bookings give 30.1% (95% CI 28.2–31.9%). Among the 1,830 calls with a booking intent, the most operationally meaningful denominator, 707 completed bookings give 38.6% (95% CI 36.4–40.9%). The full intent × outcome × booking cross-tabulation is provided in Table 7.

Table 7: Consolidated intent × outcome cross-tabulation with system-completed bookings (full dataset)

Consolidated intent	n	Success	Incompl.	Other	Bookings
Booking / Scheduling	1,830	1,799	3	28	707
Unclear / Incomplete	1,056	42	960	54	1
General inquiries	221	185	7	29	4
Human assistance	151	139	2	10	1
Emergency	121	120	0	1	5
Other	153	104	19	30	25
Total	3,532	2,389	991	152	743

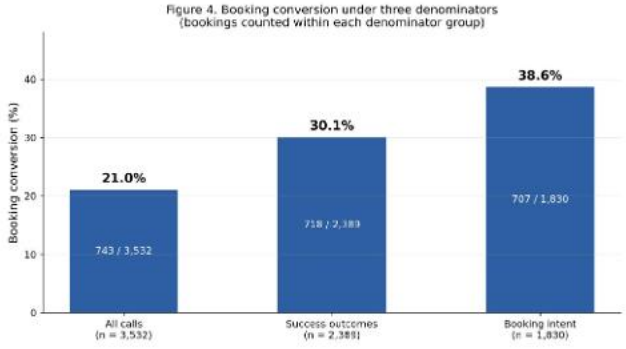

Fig. 4: Booking conversion under three denominators

When a caller arrives with the intention to book, the AI receptionist completes the booking autonomously in just under 2 of 5 cases in the observed sample. The remaining booking-intent calls did not result in a same-call booking for one of three reasons: the caller was offered slots but did not confirm before the dialogue ended, the caller requested a callback for human assistance, or the system captured the lead and deferred booking to clinic staff.

4.6 Inter-clinic Comparison

As Section 2.3 noted, call volume is concentrated in two clinics, with the eight pilot sites contributing a small residual. Fig. 5 contrasts the operational performance metrics of the two principal clinics and the aggregated pilot sites. Table 3 reports volume and structural indicators not displayed in Fig. 5.

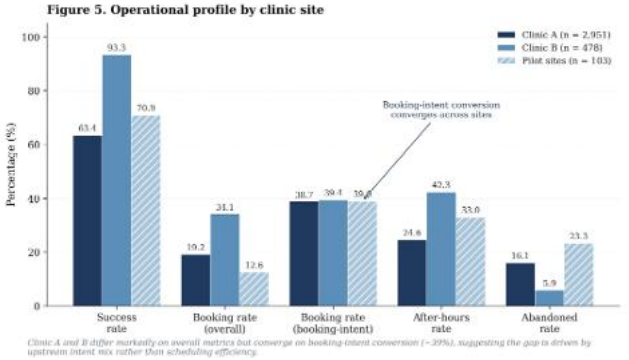

Fig. 5: Operational profile by clinic site

Table 3: Volume and structural indicators by clinic site

Metric	Clinic A	Clinic B	Pilot sites
Total calls	2,951	478	103
Incomplete rate	31.7%	5.9%	28.2%
Mean duration (s)	108.1	26.0	63.4

The two principal clinics show contrasting profiles. Clinic A handles more volume (2,951 calls) at lower success (63.4%, 95% CI 61.6–65.1%) and booking (19.2%) rates, and with a longer mean duration (108.1 seconds). Clinic B handles fewer calls (478) at a higher success rate (93.3%, 95% CI 90.7–95.2%), a higher booking rate (34.1%) and a shorter mean duration (26.0 seconds, median 0 seconds). The shorter median for Clinic B, combined with its 42.3% after-hours share, suggests that a large portion of Clinic B traffic consists of brief automated interactions resolved without extended dialogue, a pattern that fits a deployment configured for after-hours call capture. The difference in Success rates between Clinics A and B is statistically significant ($\chi^2(1) = 167.9$, $p < 0.001$, $\varphi = 0.22$). This unadjusted difference is, for the greater part, a calendar-time effect. Clinic B logged 10 calls in June–August 2025 and became active in September, whereas Clinic A logged 915 calls in those three months at a Success rate of 23.5% (215 of 915); Clinic A's aggregate therefore carries the whole pre-maturation period described in Section 4.8 and Clinic B's does not. Restricting both clinics to their common window, September 2025 to March 2026, narrows the Success gap from 29.9 to 11.8 percentage points (Clinic A 81.3%, 1,656 of 2,036, 95% CI 79.6–83.0%; Clinic B 93.2%, 436 of 468, 95% CI 90.5–95.1%; $\chi^2(1) = 38.7$, $p < 0.001$, $\varphi = 0.12$), and booking-intent conversion in the same window is identical at the two sites (40.3% and 40.4%). A

residual site difference in Success remains after this adjustment; the headline gap, however, is mostly a period effect. Of Clinic B's 478 calls, 257 (53.8%) carry a zero recorded duration at the telephony layer. Success is 87.9% among the zero-duration calls and 99.5% among the remaining 221 calls, so zero-duration records alone do not produce the clinic's aggregate 93.3%. A technical definition of zero-duration calls at the telephony layer is still missing.

When conversion is normalised to booking-intent calls only, the two clinics converge: 38.7% for Clinic A versus 39.4% for Clinic B. This convergence indicates that the gap in the overall booking rate derives from the upstream intent mix — which calls reach the system — and that booking-completion efficiency, once intent is captured, is comparable across sites. Pilot sites show similar booking-intent conversion (39.0%) but higher abandonment (23.3%), indicating that the system handles booking intent consistently across deployments and remains vulnerable to early termination in low-volume settings.

Section 4.8 assesses temporal stability directly from the dataset.

4.7 Qualitative Analysis of Dialogue Transcripts

Of the 66 transcripts extracted, 50 contained complete dialogue text suitable for content analysis. The other 16 records were short fragments, system-state messages or duplicate exports. Mean transcript length was 844 characters, with a mean of 4.7 patient turns per dialogue (median 4). Lead tagging of the 50 valid transcripts concentrated in two categories: Positive_Lead (44 transcripts, 88%) and call_back (5 transcripts, 10%), with one untagged record.

Content coding of the 50 valid transcripts identified five recurring patterns, summarised in Table 4.

Table 4: Frequency of dialogue patterns in 50 valid transcripts

Dialogue pattern	**Transcripts (n = 50)**	**Share**
Slot offering present (any time/date proposal)	13	26%
Emergency-related dialogue content	30	60%
Identity verification step (DOB / full name)	14	28%
Explicit booking confirmation utterance	9	18%
Human-handover / callback trigger	7	14%

Three findings from the qualitative analysis merit emphasis. First, the booking flow follows a four-stage structure across booking-intent dialogues: opening greeting from the AI receptionist named "Reeta AI" in the deployed configuration; classification of caller status, new versus existing patient; identity verification, full name and date of birth for existing patients; slot offering, selection and confirmation. The full sequence appears in 9 of the 50 transcripts. A time- or date-specific slot proposal appears in 13 of the 50 transcripts; the remaining dialogues ended at the intake or triage stage before any slot proposal, or involved no booking request.

Second, emergency-related interactions follow a distinct pattern that departs from the standard booking flow. In emergency cases, bleeding, severe pain or system-flagged "dental emergency", the AI receptionist confirms urgency, captures caller's name and phone number, and signals that clinic staff will contact the caller. Autonomous booking does not occur in these cases. The dialogue prioritises rapid information capture over slot assignment. The pattern aligns with the quantitative finding that only 17.3% of emergency-flagged calls result in a system-completed booking.

Third, human-escalation triggers appear in 7 of the 50 analysed transcripts, concentrated in three situations: a caller requesting a representative or callback; cases involving complaints or sensitive enquiries that the system is not authorised to resolve; handover via voicemail when the dialogue cannot complete within the AI's operational scope. These observed triggers align with the system's stated escalation policy: routing to human staff when the request is complex or sensitive, when classification confidence is low, when the caller requests a human, or when the workflow requires manual intervention.

Taken together, the qualitative findings indicate that the AI receptionist operates within a defined and observable conversational scope: a structured booking flow for routine appointments, a separate triage-and-capture protocol for emergencies, and handover paths for cases outside its remit. The patterns are consistent across the two principal clinics within the available sample.

4.8 Temporal Stability and Learning Effects

Table 8 reports monthly Success, booking-completion and abandonment rates across the full 296-day window. The series traces a steep maturation curve: in the first three months of the window (June–August 2025, n = 978) the Success rate was 26.2%, booking completion 3.3% and abandonment 21.0%, whereas in the final three months (January–March 2026, n = 1,308) Success reached 86.2%, booking completion 32.8% and abandonment fell to 9.4%. The observation window coincides with active product development, so month-level figures confound patient

behaviour with configuration and model changes; the aggregate values reported elsewhere in this section (67.6% Success, 21.0% booking completion) average over this trajectory and understate the performance of the mature system while overstating that of the early deployment. The series is not monotonic at the end of the window: March 2026, the highest-volume month in the dataset, records a lower Success rate (77.8%) and booking-completion rate (25.7%) than either January or February. The cause is not established from the available data and the decline is reported as unexplained variance.

Table 8: Monthly operational metrics across the observation window (all clinics)

Month	Calls	Success	Booking	Abandoned
2025-06	94	51.1%	2.1%	30.9%
2025-07	673	17.4%	4.0%	12.3%
2025-08	211	43.1%	1.4%	44.1%
2025-09	353	83.0%	19.0%	16.7%
2025-10	438	78.5%	18.3%	17.1%
2025-11	182	80.8%	39.0%	13.2%
2025-12	273	81.0%	23.4%	17.2%
2026-01	370	91.4%	41.9%	8.4%
2026-02	420	92.1%	33.6%	6.2%
2026-03	518	77.8%	25.7%	12.7%

V. DISCUSSION

This study combines the conceptual framework derived from healthcare chatbot, AI scheduling and dental conversational AI literature with empirical evidence from a multi-clinic deployment of an AI virtual receptionist. The discussion is organised in four parts: interpretation of the empirical findings against the published literature; implications for the proposed framework and architectural choices; practical implications for dental practices; and limitations and directions for future work.

5.1 Empirical Findings in the Context of the Published Literature

The synthesised framework positions the virtual receptionist as a central orchestrator for communication and scheduling in dental practices. The empirical patterns observed in this study support that positioning and supply practice-grounded magnitudes of a kind so far absent from the dental AI literature.

The dominance of Appointment Booking or Scheduling intent (51.8% of all calls) and the share of Emergency or Urgent Concerns (3.4% by consolidated category, 5.2% by Emergency_Flag) confirm that scheduling and triage are the two principal workloads for a dental virtual receptionist, in line with the function inventories reported by M. Barreda et al. [1] and M. Laymouna et al. [2]. The 38.6% booking conversion rate for booking-intent calls is, to the author's knowledge, one of the first published quantitative benchmarks for AI-assisted booking in real-world dental practice. Direct comparison is constrained by heterogeneous denominators in the prior literature. The magnitude aligns with the metanarrative review of AI scheduling systems by D.R.T. Knight et al. [4], which reports productivity gains and reduced provider burden across implementations using comparable real-world designs.

Healthcare chatbot reviews report that administrative and access-related uses are common. The scoping review by M. Barreda et al. [1] identifies appointment management as one of several recurring chatbot functions alongside mental health support, information delivery and lifestyle change support. In a rapid review, M. Laymouna et al. [2] divide chatbots into two categories: remote service delivery, and administrative responsibilities like appointment scheduling, referrals and data collection. In a scoping review including non-healthcare chatbots, E. Grassini et al. [3] find that about 19% of deployed chatbots are for accessing healthcare services, like booking an appointment and accessing contact information. This suggests that the booking-intent share of 51.8% observed here is considerably higher than the 19% access-related share reported by Grassini et al. The difference is expected. The present sample is drawn from a system deployed specifically to replace a dental front-desk function, so booking-related contacts are over-represented by design relative to the general-purpose healthcare chatbots surveyed in that review.

After-hours coverage was one of the most powerful signals in the analysis. After-hours calls, 27.3% of the total, reached almost the same Success rate as business-hours calls (66.9% versus 67.9%); the within-clinic comparison in Section 4.3 shows the same closeness at both principal sites, with a 4.9-point after-hours deficit at Clinic A. This aligns with the access barriers recognised in the inclusive-healthcare review literature [3] and an access-oriented framing of multimodal chatbots [13]. The pre-implementation practitioner-reported gap of 80–120 unhandled calls per month, with 40–60% follow-up failure for after-hours interactions, falls in the same order of magnitude as the post-implementation handling of around 97 after-hours calls per month observed in this study. The comparison is directional and not statistical. It indicates that AI-driven receptionists can close the most common operational gap reported by clinic operators, overnight and

early-morning calls that historically went to voicemail or were dropped.

The quality and safety of patient-facing materials must be governed. H. Esmailpour et al. have shown that AI chatbots can produce responses of high quality to most FAQs in prosthodontics, but produce low quality responses to a small subset of these questions [10]. The same study reports that some chatbot outputs demand a high reading level and remain hard for patients to follow [10]. E.E. Maruska et al. [11] report comparable informativeness between chatbot and dentist answers, with machine output at times matching or exceeding dentist accuracy while offering less empathy and context. The empirical finding that emergency-flagged calls reached a Success outcome in 98.9% of cases while only 17.3% ended with autonomous booking matches a system constrained to capture-and-handover behaviour for sensitive cases, a design pattern that aligns with the cautionary recommendations in the dental conversational AI literature. The qualitative observation that 7 of the 50 analysed dialogues exhibited human-escalation triggers reinforces this interpretation: the system is designed to recognise its operational scope and route out-of-scope cases to human staff.

The 29.9% share of Unclear or Incomplete Intent, of which 47.5% are also abandoned, is the largest single source of unrealised potential in the dataset. The pattern of short duration, abandonment without dialogue and no confident intent assignment points to a class of interactions where intent capture itself is the bottleneck. Improving the opening turn of the dialogue (lower latency, refined prompt phrasing, graceful handling of early caller hang-ups) may yield disproportionate gains, in line with the engineering attention to prompt and dialogue design highlighted by Shaikh et al. [13] and Alsalamah et al. [9].

The scheduling aspect was discussed in the context of appointment scheduling systems [5, 6] in the metanarrative study by D.R.T. Knight et al. [4] on AI for patient scheduling systems with no-shows, dynamic sequencing of patients, and dynamic capacity planning of clinical appointments. The authors found heterogeneity in models and outcomes. AI scheduling can reduce the workload of providers and increase productivity when implemented in clinical workflows. Most reviewed systems operate in hospitals or outpatient settings instead of dental practices. The underlying principles, probabilistic modelling of attendance, optimisation of slot allocation under resource constraints, and integration with electronic systems, transfer to multi-chair dental clinics. The proposed framework incorporates predictive and optimisation logic in its scheduling layer, while leaving clinical approval and final decision-making to humans. The empirical convergence of booking-intent conversion across the two principal clinics (38.7% and 39.4%) indicates that the scheduling component performs consistently when intent is well captured, and that residual variation between sites stems from upstream factors, such as intent mix, call duration profile, and deployment configuration.

Comparing different strands of evidence clarifies how benefits cluster and where uncertainties remain. Table 5 indicates that benefits cluster around efficiency, access and experience, with direct implications for dental reception workflows.

Table 5: Reported benefits of chatbots and AI scheduling relevant to a dental virtual receptionist [1, 2, 9, 10, 12–14]

Primary setting	**Function relevant to reception**	**Reported benefit type**
Virtual hospital / virtual care	Person-centred conversational triage and coordination	Shorter consultation times, improved clinician–patient communication, higher patient satisfaction, enhanced workflow indicators
Multiple healthcare domains	Appointment management, patient information, and monitoring	More efficient delivery of remote services, potential cost savings, and improved access to services
Dental prosthodontics	Automated answering of patient FAQs	High average response quality, improved accessibility of information, and better readability for some models
Post-operative follow-up	Automated follow-up and symptom monitoring	High response rates, sustained engagement, and reduced need for in-person follow-up contact
eHealth applications	Access to healthcare, appointment booking, and remote assistance	Expanded access for remote and underserved users, potential reduction in organisational burden
Real-world healthcare scheduling	AI-based patient scheduling	Reduced provider burden, increased productivity, and opportunities for better slot utilisation
Broad healthcare landscape	Administrative assistance, remote services	Greater accessibility, potential for more efficient care pathways, and a wide range of user groups served

General healthcare	Multimodal conversational support and appointment module	Streamlined intake and appointment scheduling, reduced administrative workload, improved patient access
Dental education	Structured diagnostic and communication dialogues	High user satisfaction, perceived improvement in diagnostic reasoning and communication skills

Evidence from VHC-Bot and the AI Healthcare Chatbot indicates that conversational systems shorten consultation time while sustaining or improving patient satisfaction [9, 13]. Remote-service reviews report that chatbots sustain engagement in follow-up scenarios [1, 2, 14], and dental-specific work demonstrates that chatbots convey clinically relevant information at acceptable quality [10–12]. Set against these gains are documented limitations and risks reported across the literature (Table 6).

Table 6: Principal risks and limitations of healthcare chatbots aligned with dental virtual receptionist use [2–4, 9–11]

Risk or limitation type	**Relevance to the dental virtual receptionist**
Occasional poor-quality, misleading responses; variable readability	Requires content governance, constrained domains, and readability tuning for dental FAQs
Limited attention to accessibility and inclusion in many implementations	Necessitates explicit accessibility requirements (screen readers, plain language, multilingual support) for reception interfaces
Heterogeneous models and metrics; limited real-world evidence on long-term sustainability	AI scheduling components should be monitored for unintended effects on access and fairness; human oversight is needed for policy decisions
Ethical, medicolegal, and user-experience concerns; risk of overreliance	Dental clinics must communicate chatbot limits, log interactions, and design clear escalation to human staff
Lower empathy and inconsistent nuance compared with dentists	Virtual receptionists should be restricted to administrative and low-risk informational tasks; sensitive discussions should stay with clinicians
Risk of clinician deskilling and unsafe self-diagnosis if AI is overused	System design should preserve clinician authority and avoid autonomous clinical decision-making in scheduling and triage

5.2 Implications for the Framework and Architecture

The empirical findings reinforce three architectural choices outlined in Section III.

First, the four-layer decomposition of the framework, multichannel intake, conversational understanding and triage, scheduling and workflow orchestration, and oversight, logging and analytics, maps onto the empirical patterns in a usable way. The intake and conversational layers are stress-tested by the share of Unclear / Incomplete intent and abandoned short calls. The scheduling layer converts ≈ 39% of booking-intent calls into confirmed bookings across deployments. The oversight layer is operationalised by the structured outcome and intent fields in the dataset. The analytical telemetry envisaged by the framework is therefore realisable in production.

Second, the empirical Emergency-handling pattern, high Success rate, combined with low autonomous booking rate and elevated dialogue duration, supports the framework's emphasis on defined escalation rules and on human oversight for high-priority cases. The pattern aligns with the operational stance described by the system operator: calls escalate when the request is complex or sensitive (such as emergencies or complaints), when classification confidence is low or ambiguity is detected, when the caller requests a human, or when the workflow requires manual intervention. Emergency-related scenarios follow strict escalation protocols for patient safety. The incidence of human-handover triggers in 7 of the 50 analysed transcripts indicates that escalation is an observable component of system behaviour, not a theoretical fallback.

Third, the system architecture as described by the operator, a hybrid configuration combining large language models, accessed via providers such as OpenAI, with real-time speech-to-text processing, dental-workflow-tuned intent detection, context-aware response generation, workflow automation and rule-based orchestration for safety and operational control, matches the modular pattern proposed in the framework and the multimodal modular architectures described by Shaikh et al. [13] and Alsalamah et al. [9]. The combination of generative and rule-based

components carries weight in the empirical pattern: emergency dialogues follow a tightly bounded capture-and-handover pattern that differs from the more flexible booking flow, which indicates that rule-based orchestration enforces the safety boundaries the literature has called for.

5.3 Practical Implications for Dental Practices

From a systems-engineering perspective, dental clinics form a favourable environment for such a framework. They operate with fewer integration layers than hospitals because practice management systems oversee scheduling, billing, and clinical documentation. The AI scheduling insights reported by Knight et al. [4] can be embedded as decision-support services. A no-show prediction model, for example, proposes an overbooking range. The receptionist assistant suggests rescheduling low-priority visits without mandating it, preserving clinician and manager oversight while drawing on patterns extracted from historical data.

In this setting, the AI receptionist functions as a dispatcher for several patient queues, where requests are classified, assigned priority weights and routed to constrained resources such as chairs, providers and communication channels. Queue-based scheduling and optimisation-driven appointment allocation form a structured approach to relieving workflow bottlenecks caused by ad hoc booking rules and manual triage at the front desk. The empirical observation that Friday and the 10:00–12:00 window jointly carry a disproportionate share of weekly volume (29.5% of weekly traffic concentrated in a single weekday; 31.1% of daily traffic concentrated in a three-hour morning window) supplies an operational argument for AI-driven load smoothing and priority queuing during peak intervals.

Another dimension concerns staff experience. Front-desk teams in dental practices handle multiple concurrent tasks, including phone communication, arrivals, insurance checks and coordination with clinicians. Research on chatbots and virtual care, such as work by Alsalamah et al. [9], Barreda et al. [1], Laymouna et al. [2] and Shaikh et al. [13], shows that the automated management of routine, low-judgment tasks using a configured virtual receptionist that can process out-of-hours requests, reschedule appointments using a self-service option, and provide standard information messages reduces demand peaks. This allows staff to focus on more difficult situations, such as distressed patients or complicated insurance questions. Research on automating administrative responsibilities in healthcare has reached similar conclusions that scheduling and inquiries are good candidates for automated support [2, 4]. The empirical 27.3% after-hours share confirms that this displacement effect is observed in practice. It represents one in four interactions absorbed without consuming staff time during business hours.

Converting informal booking heuristics into transparent optimisation rules gives clinics a tunable mechanism for balancing high-priority and routine visits. Priority-weighted triage ordering moves clinically urgent or time-sensitive cases through the reception queue without permanently displacing preventive and elective care. The empirical pattern that emergency-flagged calls are uniformly resolved (98.9% Success) and routed via human-handover (only 17.3% autonomous booking) shows this priority logic operating in practice.

For dental patients in underserved, rural or mobility-restricted groups, the framework promises smoother access to appointments and information. Reviews focused on access to care and inclusivity describe chatbots' capacity to mitigate barriers when physical attendance or traditional communication channels are limited [1–3]. Adapted for dentistry, a virtual receptionist that supports text, voice, and multiple languages lowers entry barriers for individuals who experience difficulties with phone communication during working hours or find conventional booking methods inconvenient. The current dataset shows concentration in English (99.3% of identified-language calls) and a phone-first channel mix. The multilingual and multichannel capacity of the framework, remains untested at scale in this sample and is a target for future evaluation.

5.4 Limitations

Several limitations of the empirical component should be borne in mind when interpreting the findings.

First, the absence of a formally logged pre-implementation baseline restricts the analysis to post-implementation description. The practitioner-reported estimates of 80–120 unhandled calls per month and a 40–60% follow-up gap before AI deployment serve as a directional reference and cannot support a statistical before-and-after test. Future work in clinics that retain detailed historical call-handling logs would enable more rigorous comparisons.

Second, the concentration of call volume in two clinics limits the generalisability of inter-clinic patterns. The within-clinic patterns observed in Clinics A and B carry weight given the sample size. The eight pilot sites are too small individually to support per-site analysis. Aggregating pilot sites mitigates this constraint without removing it.

Third, the study does not include a controlled comparison group. The system under evaluation is a commercially deployed product, and the practical and ethical constraints of running a randomised trial of front-desk automation in active clinics are considerable.

Observational evidence from real-world deployment is the best available alternative and cannot rule out confounding factors such as concurrent practice management changes, staffing levels, or seasonal variation.

Fourth, the unpopulated Escalated_To_Human_Flag field required proxy measurement of human-handover events using a combination of Lead_Tag, Callback_Requested_Flag, and intent category. The approach yields a lower bound on escalations and does not capture cases in which staff intervened without these flags being set. Tighter telemetry on escalation events is a target for future iterations of the data layer.

Fifth, the qualitative coding of 66 transcripts was performed by a single coder against a predefined frame. Inter-rater reliability was not assessed. The aggregated counts in Table 4 should be interpreted as descriptive measurements.

Sixth, the analysis is restricted to calls handled by one commercial system within a specific deployment context. Findings on intent distribution, conversion rates, and dialogue patterns may not generalise to dental practices using different conversational AI systems, practice-management integrations, or patient populations. The framework set out in Section III is system-agnostic. The empirical evidence presented here is system-specific. Seventh, the system under evaluation assigns every analytic label in this study (Intent_Category, Outcome_Status, Emergency_Flag, Booking_Completed_Flag); no independent human coder or practice-management-system record has validated them. The findings describe system-recorded outcomes, and Booking_Completed_Flag captures system-side completion only: no check confirmed that each booked appointment existed in the practice management system and was kept. A rule-based cross-check of transcript-level fields (Section 2.7) found full agreement on emergency content and moderate agreement on callback tagging, but Intent_Category and Outcome_Status remain unvalidated. Eighth, hour-of-day figures assume that Call_Start_Timestamp and the derived Hour_of_Day follow each clinic's local time zone. Inspection of the raw exports found mixed timestamp formats, including records with explicit UTC markers, and a seasonal shift in the within-clinic hourly profile that daylight-saving transitions do not explain. The paper reports the 04:00–07:00 after-hours concentration as recorded clock time and reads no early-morning caller behaviour into it. The calls themselves are substantive: Success reaches 76.9% and booking completion 27.3% in this window, against 65.5% and 19.6% elsewhere.

Ninth, certain fields in the dataset (New_Patient_Flag, Existing_Patient_Flag) were left blank, preventing direct quantification of the new-versus-existing patient mix relevant to booking behaviour. The 28% incidence of identity-verification steps in transcripts gives indirect evidence on this dimension. A structured analysis would require populated patient-status fields.

The discussion of evidence indicates that an AI-driven virtual receptionist configured according to the proposed framework aligns with current trajectories in healthcare chatbots, schedule optimisation and digital dentistry, and that the empirical patterns observed in commercial operation align with the published literature in both magnitude and qualitative shape. The approach aligns with the direction of emerging commercial systems focused on dental communication and scheduling automation, grounded in published evaluations and now supported by real-world operational data.

VI. CONCLUSION

The article develops and empirically substantiates an AI-driven virtual receptionist framework that adapts healthcare chatbot and AI scheduling research to the operational realities of dental practices. The framework integrates multichannel conversational intake, domain-constrained large language models and a scheduling layer informed by AI-based patient scheduling studies, with provisions for human oversight, accessibility and content quality control.

The first objective, systematising current evidence, was met by combining healthcare-wide chatbot reviews, AI scheduling syntheses and dental-specific evaluations of conversational systems. The second objective, constructing a conceptual architecture, draws on recent designs for multimodal chatbot systems and person-centred virtual care platforms specialised for dental scheduling and administrative triage. The third objective, empirical evidence on workflow effects, rests on a 9.9-month observational dataset of 3,532 calls and 66 extracted dialogue transcripts (50 analysed) across ten dental sites, two of which were studied in depth.

The empirical findings indicate that in commercial deployment the AI virtual receptionist absorbs a measurable share of administrative call volume (67.6% Success outcomes overall, 38.6% booking conversion among the 1,830 booking-intent calls, 27.3% after-hours coverage), keeps a separation between routine booking workflows and emergency triage (the latter resolves in 98.9% of cases through capture-and-handover instead of autonomous booking), and exhibits identifiable human-escalation patterns in 7 of the 50 analysed dialogues. Booking-intent conversion is consistent across the two principal clinics (38.7% and 39.4%), although their overall Success rates differ in the unadjusted comparison, a gap

that is mostly a calendar-time effect and narrows from 29.9 to 11.8 percentage points once both clinics are restricted to the months they share (Sections 4.6 and 4.8), and the findings align with conceptual expectations drawn from the published literature. These aggregates span a period of active development: in the final three months of the window the system reached 86.2% Success and 32.8% booking completion, against 26.2% and 3.3% in the first three (Section 4.8).

For dental practices and technology providers, the framework offers a set of design and governance principles anchored to a real-world operational profile. It supports incremental adoption, starting with self-service booking and FAQs and progressing toward integrated triage of routine requests and data-driven scheduling proposals. The empirical observation that booking-intent conversion converges to ≈ 39% across deployments while overall conversion varies widely shows that the principal lever for performance gains lies upstream, in intent capture, opening-turn design and reduction of short abandoned interactions, and not in the scheduling logic itself.

Future empirical work can build on this conceptual and empirical foundation through controlled before-and-after comparisons in clinics with detailed historical call logs, evaluation of multilingual and multichannel performance in linguistically diverse populations, and quantification of staff-time displacement and patient-experience effects through primary survey instruments. Targeted improvements to operational telemetry, including populating the escalation, patient-status, and language fields, would enable deeper analyses than the current data layer permits.

Viewed through an operations management lens, the virtual receptionist serves as an optimisation-driven control layer atop existing practice management infrastructure. Data from intake, triage and historical attendance feed into appointment-allocation models that smooth demand, reduce idle time and compress avoidable waiting. Progressive deployment of such systems offers a path toward measurable gains in workflow efficiency and toward data-informed resource allocation in dental practice operations.

CONFLICT OF INTEREST

The author is the CEO and Co-Founder of DentalAssist.ai, the commercial system evaluated in this study. The analysis was conducted on anonymised operational data and all findings are reported in aggregate form. This affiliation is disclosed in the interest of transparency.

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Innovation Management and Critical Success Factors in the Brazilian Insurance Market: A Comprehensive Empirical Framework, Sectoral Diagnostic, And Strategic Execution

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***Keywords*— Innovation Management; Insurance Market; Critical Success Factors; Organizational Maturity; Strategic Execution Gap**

***Abstract*—** *Innovation has transitioned from a tactical option to a fundamental strategic imperative for continuous corporate survival, sustainability, and competitive differentiation in the global financial services industry. However, contemporary academic literature lacks a comprehensive, empirical diagnostic framework tailored specifically to emerging markets such as the Brazilian insurance sector. This domain is uniquely characterized by strict state-level oversight under the Superintendence of Private Insurance (SUSEP) and National Council of Private Insurance (CNSP), high economic concentration among major banking and insurance conglomerates, and a historically low market penetration index relative to Gross Domestic Product (GDP). The primary objective of this study is to formulate, structure, and exploratorily assess a multi-dimensional conceptual framework for mapping, measuring, and evaluating critical success factors (CSFs) and organizational practices for innovation in insurance companies operating within Brazil. The methodology comprised a rigorous, systematic literature review spanning international and national academic databases, which grounded the identification, qualitative synthesis, and consolidation of 34 critical practices organized into six thematic dimensions: (1) Innovation Governance, (2) Organizational Culture, (3) Innovation Management, (4) Risks and Compliance, (5) Enabling Technologies, and (6) Human Resources and Innovation Structures. Based on this framework, a dual 5-point Likert scale diagnostic tool was engineered to capture executive perceptions regarding Strategic Relevance (Very Low to Very High) alongside actual operational Adoption Level (Not Used to Plenary). The instrument was exploratorily assess through a field pilot study engaging*

executive leaders across four representative insurance companies displaying distinct structural and market profiles. The empirical findings confirmed the universal applicability of the framework (85.3% of items rated as 100% applicable) while revealing a critical strategic execution gap: whereas cloud computing, digital platforms, and Application Programming Interfaces (APIs) demonstrate advanced to plenary adoption, foundational managerial dimensions—specifically Innovation Governance, Structured Ideation Processes, Change Management, and Risk Culture—exhibit incipient or intermediate maturity despite being rated with unanimous high strategic relevance by C-level executives. The study contributes a examined in a pilot organizational diagnostic artifact capable of measuring the gap between declared strategy and practical execution, providing executive guidance for resource allocation and laying a rigorous foundation for future large-scale academic research.

I. INTRODUCTION

■ 1.1 Contextualization and Research Problem

The accelerated digitalization of the global economy, combined with rapid shifts in consumer expectations and macroeconomic volatility, has imposed an unprecedented demand for continuous transformation across products, processes, and business models in financial services. In the insurance domain, corporate innovation is no longer a discretionary activity reserved for market leaders; it has evolved into a fundamental determinant of corporate survival, growth, and long-term organizational resilience [1, 2]. The insurance sector fulfills a vital macroeconomic function by acting as an indispensable pillar of financial stability, capital allocation, credit enhancement, and systemic risk mitigation [3]. However, traditional underwriting, actuarial, and distribution paradigms face severe disruption from technological convergence, demographic shifts, and evolving risks such as cyber threats, climate change, and public health emergencies [4].

While international academic literature regarding innovation management is voluminous, a prominent theoretical and empirical gap persists concerning its direct application to emerging markets, particularly the Brazilian insurance industry. The national market possesses marked structural specificities, including strict state-level regulation overseen by the Superintendence of Private Insurance (SUSEP) and the National Council of Private Insurance (CNSP), high market concentration among banking and insurance conglomerates, and a historically low market penetration index relative to Gross Domestic Product (GDP) when compared to mature Western economies [5, 6].

Previous research has examined innovation capabilities, interorganizational cooperation, and knowledge management in Brazilian firms, including financial services and insurance organizations [7, 8]. Nevertheless, an important question remains insufficiently addressed: how can organizations systematically assess the alignment between the strategic importance attributed to innovation practices and their actual level of implementation? This study addresses this question by developing a multidimensional diagnostic framework that integrates organizational, technological, and regulatory perspectives within the Brazilian insurance industry.

Despite the growing recognition among industry executives regarding the necessity of digital transformation, empirical research indicates that many organizations encounter substantial bottlenecks when attempting to operationalize corporate innovation strategies. Existing frameworks often focus on isolated technology adoption or general managerial practices without accounting for the regulatory, structural, and cultural constraints peculiar to insurance firms in emerging economies. Consequently, there is an urgent academic and managerial requirement to systematically map, categorize, and evaluate the internal organizational capabilities, governance mechanisms, cultural drivers, and technological enablers that drive innovation success in this environment.

1.2 Research Questions and Objectives

Addressing this theoretical and practical gap, this study investigates the central research question: "Which organizational factors and practices contribute most to the success of innovation in the Brazilian insurance market?"

To address this question, the primary objective of this research is to formulate, structure, and empirically validate a comprehensive conceptual framework for mapping and evaluating critical success factors and organizational practices for innovation in insurance companies operating in Brazil. As secondary objectives, the study aims to:

- 1. Systematize Literature: Synthesize international and national academic literature to categorize key organizational capabilities into six thematic dimensions.
- 2. Develop Diagnostic Tool: Create a dual-perspective diagnostic instrument capable of capturing executive perceptions of strategic relevance and operational implementation maturity across organizations.
- 3. Conduct Empirical Pilot: Execute a field pilot study with operating insurers in Brazil to evaluate instrument clarity, applicability, and diagnostic capabilities.
- 4. Identify Strategic Execution Gaps: Pinpoint internal bottlenecks and misalignments between declared corporate innovation strategies and practical operational execution.

The remainder of this paper is structured as follows: Section 2 presents the theoretical foundations and structural scenario of innovation in the Brazilian insurance market. Section 3 outlines the methodological approach and research design. Section 4 presents the comprehensive taxonomy of the 34 critical success factors. Section 5 discusses the empirical results of the pilot diagnostic study. Finally, Section 6 synthesizes conclusions, managerial implications, study limitations, and future research directions.

II. THEORETICAL FOUNDATIONS AND SECTORAL SCENARIO

■ 2.1 Theoretical Foundations of Corporate Innovation Management

In the Brazilian insurance industry, [8] examined open innovation, knowledge management, and organizational competitiveness. Their investigation provides sector-specific grounds for considering innovation beyond the adoption of digital technologies, encompassing the mobilization of knowledge, organizational capabilities, and interactions among participants in innovation processes. Building on this perspective, the present study extends the analytical focus toward the systematic assessment of innovation-related practices and their reported implementation maturity across organizational dimensions.

Corporate innovation is conceptualized by the Organization for Economic Co-operation and Development (OECD) as the implementation of a new or significantly improved product (good or service), process, marketing method, or organizational practice within business operations, workplace organization, or external relations [9, 10]. [2] build upon these foundations by postulating that innovative capability serves as the primary engine driving sustainable competitive advantage, operational efficiency, product portfolio expansion, customer satisfaction, and organizational resilience across dynamic markets. Their foundation "4Ps Model of Innovation" categorizes organizational transformation into four distinct vectors:

- Product Innovation: Changes in the things (products or services) an organization offers.
- Process Innovation: Changes in the ways in which products and services are created and delivered.
- Position Innovation: Changes in the context in which products and services are introduced and framed in the market.

Paradigm Innovation: Changes in the underlying mental models which frame what the organization does.

In established corporations, implementing innovation presents distinct structural challenges. [11] proposes the "Three-Box Solution" framework to balance short-term operational excellence with long-term transformation:

- Box 1 (Manage the Present): Optimizing the core business that generates current cash flow, profitability, and operational stability.
- Box 2 (Selectively Forget the Past): Abandoning practices, assumptions, legacy architectures, and business models that no longer serve future growth.
- Box 3 (Create the Future): Developing breakthrough innovations, new capabilities, and long-term business models.

Furthermore, [12] emphasizes that the Fourth Industrial Revolution is characterized by a fusion of physical, digital, and biological technologies—including Artificial Intelligence (AI), the Internet of Things (IoT), Cloud Computing, and Robotics—operating at an exponential rather than linear pace. In emerging digital contexts, [13] highlights that successful digital inclusion and technology adoption depend on three interconnected dimensions: Access (infrastructure and connectivity), Capacitation (skills and training), and Attitude (cultural readiness and user willingness). In generative AI contexts, [14] categorize corporate AI innovation strategies into four operational quadrants based on the interplay of automation and augmentation: Traditional Tools (low automation, low augmentation), Basic Automation (high automation, low augmentation), Automated Assistance (low automation, high augmentation), and Assisted Augmentation (high automation, high augmentation).

■ 2.2 Transformation Drivers in the Insurance Industry

Global and national insurance industries fulfill a vital macroeconomic function by acting as essential pillars of financial stability, capital allocation, credit enhancement, and systemic risk mitigation [3]. However, traditional underwriting and actuarial paradigms face severe disruption from four convergent transformation vectors:

1. Insurtech Disruption: Technology-driven startups redefining digital customer journeys, automated underwriting, and distribution ecosystems [15].

2. Product Customization Demand: Growing consumer expectation for flexible, pay-per-use, usage-based insurance (UBI), and personalized coverage models [16]. [13] emphasizes that adoption depends on Access, Capacitation, and Attitude, supported by Brazilian household internet access reaching 92.5% [17].

3. Regulatory Modernization: Initiatives such as the Regulatory Sandbox (SUSEP) and Open Insurance regulation (CNSP Resolution No. 415/2021, Law No. 15,040/2024), which foster experimentation under regulatory supervision [18, 19].

4. Emerging Risk Profiles: The requirement for novel underwriting solutions to cover cyber threats, climate-related risks, and complex digital ecosystems [20, 21].

■ 2.3 Structural Features and Macroeconomic Metrics of the Brazilian Market

The Brazilian insurance market exhibits unique structural, macroeconomic, and competitive characteristics that dictate the pace, orientation, and barriers of organizational innovation. A rigorous empirical review of official market data published by SUSEP and IBGE establishes the following baseline parameters:

- GDP Penetration & Growth Potential: Total written premiums in Brazil demonstrate consistent growth, outpacing overall GDP expansion. In 2023, written premiums reached R$ 175.4 billion (~1.62% of GDP), expanding further to R$ 191.5 billion in 2024 (~1.63% of GDP) [22, 23]. This penetration index is significantly lower than mature markets like the US (10%) or UK (8%), signaling substantial growth potential [5].
- High Market Concentration: The top 12 economic groups account for roughly 70.35% of total written premiums nationwide, led by major banking and insurance conglomerates (Porto Seguro, BB Mapfre, Bradesco, Tokio Marine, Mapfre, Caixa, Allianz) [22].
- Product Line Concentration: Traditional lines such as Automobile Hull, Credit Life (Prestamista), Group Life, and Auto Third-Party Liability (RCFV) account for over 60% of total market premium, indicating major opportunities for expansion into emerging commercial, cyber, and environmental lines. etc.

Table 1. Macroeconomic Trajectory of Written Premiums vs. GDP in Brazil (2017–2024)

Year	Written Premiums (R$ Mi)	Growth (%)	Brazil GDP (R$ Mi)	Premiums/GDP (%)
2017	R$ 98,960	5.9%	R$ 6,585,479	1.50%
2018	R$ 105,085	6.2%	R$ 7,004,141	1.50%
2019	R$ 111,450	6.1%	R$ 7,389,131	1.51%
2020	R$ 116,509	4.5%	R$ 7,609,597	1.53%
2021	R$ 132,759	13.9%	R$ 9,012,142	1.47%
2022	R$ 161,030	21.3%	R$ 10,079,677	1.60%
2023	R$ 175,407	8.9%	R$ 10,856,112	1.62%
2024	R$ 191,517	9.2%	R$ 11,744,709	1.63%

Source: [22].

Table 2. Top 12 Insurance Groups by Written Premium Revenue in Brazil (2023)

Rank	Economic Group / Conglomerate	Written Premiums (R$ Mi)	Share (%)
1	PORTO SEGURO	R$ 21,026	11.99%
2	BBMAPFRE	R$ 17,167	9.79%
3	BRADESCO	R$ 12,892	7.35%
4	TOKIO MARINE	R$ 12,147	6.93%
5	MAPFRE	R$ 10,245	5.84%
6	CAIXA ECONÔMICA	R$ 9,074	5.17%
7	ALLIANZ	R$ 8,762	5.00%
8	ZURICH SANTANDER	R$ 7,068	4.03%
9	LIBERTY	R$ 7,024	4.00%
10	ITAÚ	R$ 6,332	3.61%
11	ZURICH	R$ 5,982	3.41%
12	TALANX AG	R$ 5,683	3.24%
Top 12 Total Subtotal		**R$ 123,402**	**70.35%**
Total Market (58 Groups)		**R$ 175,407**	**100.00%**

Source: [23].

Table 3. Product Line Distribution of Written Premiums in Brazil (2023)

Insurance Line / Segment	Written Premiums (R$)	Market Share (%)
Automobile - Hull (Casco)	R$ 36,756,144,792	20.95%
Credit Life (Prestamista)	R$ 16,135,864,939	9.20%
Group Life (Vida em Grupo)	R$ 15,428,946,747	8.80%
Auto Liability (RCFV)	R$ 12,078,333,241	6.89%
Named & Operational Risks	R$ 7,680,019,070	4.38%
Personal Accidents	R$ 6,826,814,270	3.89%
Auto Assistance & Other Coverages	R$ 6,150,623,030	3.51%
Agricultural Insurance (Non-FESR)	R$ 5,607,611,924	3.20%
All Other Lines Combined	R$ 68,742,639,351	39.18%
Total Market Revenue	**R$ 175,406,997,364**	**100.00%**

Source: [22].

- **Regulatory Sandbox & Open Insurance:** Established by Complementary Law No. 182/2021 (Startups Legal Framework) and CNSP Resolution No. 381/2020, the Regulatory Sandbox provided temporary regulatory relief for innovative insurance ventures [24, 25]. Simultaneously, CNSP Resolution No. 415/2021 and SUSEP Circular No. 635/2021 enacted Open Insurance across three phased implementation stages (Phase 1: Public Data Sharing; Phase 2: Personal & Policy Data Sharing; Phase 3: Transactional Execution Services), forcing traditional insurers to adopt open API architectures and interoperable digital platforms [26, 27].
- **Sectoral Innovation Investment:** According to [28], Brazilian insurers invested approximately R$ 16.7 billion in innovation and technology in 2023 (~2.5% of gross revenue), projecting R$ 19.6 billion for 2024 (~2.63% of gross revenue). Primary investment concentrated on distribution management (18%), IT back-office infrastructure (16%), and customer service (14%).

III. METHODOLOGICAL APPROACH

This research followed a rigorous, mixed-methods approach structured in three sequential phases:

- **Phase 1:** Systematic Literature Review & Factor Identification: An extensive investigation across international and national academic databases (Scopus, Web of Science, CAPES, Google Scholar) alongside institutional market reports (SUSEP, CNSEG, OECD, World Economic Forum) identified an initial pool of over 90 candidate factors. Through qualitative content analysis, these were filtered and consolidated down to 34 critical success factors and practices [29, 30].
- **Phase 2:** Categorization into 6 Conceptual Dimensions: The 34 consolidated items were organized into six thematic dimensions: (1) Innovation Governance, (2) Organizational Culture, (3) Innovation Management, (4) Risks and Compliance, (5) Enabling Technologies, and (6) Human Resources and Innovation Structures.
- **Phase 3:** Diagnostic Instrument Architecture & Empirical Field Pilot: A dual 5-point Likert scale diagnostic instrument was engineered [31] to capture executive perceptions across two distinct vectors:
  - Scale 1: Strategic Relevance: Very Low (VL = 1), Low (L = 2), Medium (M = 3), High (H = 4), Very High (VH = 5).
  - Scale 2: Adoption Level Maturity: Not Used (NU = 1), Incipient (IN = 2), Intermediate (IT = 3), Advanced (AV = 4), Plenary (PL = 5).

The diagnostic instrument was administered in an empirical field pilot study engaging executive leaders (C-level executives and senior innovation directors) across four representative insurance companies operating in Brazil, displaying distinct structural, capital origin, and product market profiles.

Because the field application involved only four organizations and one executive respondent per organization, it was treated as an exploratory pilot rather than a representative sector-wide survey or a psychometric validation. The two five-point response scales provide ordinal self-reported assessments; comparisons between their numerical scores are descriptive and should not be interpreted as precise interval-scale measurements. The study does not establish causal relationships or population-level estimates.

IV. COMPREHENSIVE TAXONOMY OF THE 34 CRITICAL SUCCESS FACTORS

4.1 Dimension 1: Innovation Governance

Strategic Alignment: Alignment of innovation strategy with general corporate strategy, ensuring

resource allocation directly serves overarching corporate goals [32].

Structured Ideation & Stage-Gate Processes: Formal, structured processes covering the entire innovation lifecycle from idea generation and screening to commercialization and scale [33].

Metrics & Performance Targets: Systematized lag and lead key performance indicators (KPIs) to track process efficiency, financial returns, and portfolio health [34, 35]..

4.2 Dimension 2: Organizational Culture

Leadership Commitment: Active engagement, advocacy, and direct support from senior executive leadership for innovation initiatives [36].

Risk Tolerance & Learning from Failure: Organizational openness to calculated risk-taking and psychological safety to treat failures as learning opportunities [2] .

Incentives & Recognition Systems: Formal reward mechanisms, financial incentives, and career recognition for employee contributions to innovation [37, 38].

Knowledge Management: Systematic mechanisms for capturing, codifying, disseminating, and applying organizational knowledge [39, 40].

Clear Strategy Communication: Transparent, continuous communication of corporate innovation goals and priorities across all organizational levels [33].

4.3 Dimension 3: Innovation Management

Internal Process Optimization: Continuous application of innovation tools to streamline operations, eliminate waste, and boost productivity [2].

Organizational Change Management: Structured strategies, stakeholder engagement, and empathetic leadership to manage transformations and overcome internal inertia [41, 42].

Employee Capacitation & Training: Ongoing professional development programs to equip staff with emerging digital and methodical skills [43].

Cross-Sector Benchmarking: Systematic comparative studies against direct competitors and cross-industry leaders to capture best practices [33].

Post-Mortem Failure Reviews: Structured evaluation of past failed projects to extract actionable lessons and refine future execution [44].

4.4 Dimension 4: Risks and Compliance

Risk-Compliance-Innovation Balance: Balancing regulatory compliance, capital solvency, and internal controls with innovative flexibility [34].

Proactive Venture Risk Management: Early identification, assessment, and mitigation of digital, cyber, operational, and reputational risks in new ventures [33].

SUSEP Regulatory Sandbox Participation: Active participation in or strategic monitoring of regulatory experimental environments [24, 25].

4.5 Dimension 5: Enabling Technologies

Machine Learning & Big Data Analytics: Advanced statistical algorithms and big data pipelines for actuarial pricing, fraud detection, and customer segmentation [45, 46].

Conversational Chatbots: Natural language processing agents for automated customer support, claims intake, and lead generation [47].

Robotic Process Automation (RPA): Software robotics automating repetitive, rules-based back-office tasks across legacy IT systems [48, 49].

Autonomous AI Agents: Self-directed AI agents capable of multi-step decision-making, complex workflow orchestration, and dynamic task execution [50, 51].

Telematics & Internet of Things (IoT): Connected sensors, telematics devices, and wearables enabling real-time monitoring and Usage-Based Insurance (UBI) [52, 53].

Blockchain & Smart Contracts: Immutable distributed ledgers and self-executing smart contracts for automated claims clearing and fraud prevention [54].

Drones & Unmanned Aerial Vehicles: Aerial imaging devices for rapid remote inspection of property, agricultural, and infrastructure damage [55, 56].

Cloud Computing: Scalable, flexible cloud infrastructure providing elasticity and rapid application deployment [57].

Digital Insurance Platforms: Integrated multi-sided digital ecosystems connecting policyholders, brokers, and service providers [58].

Insurtech Partnerships: Strategic collaboration, joint ventures, or corporate venture investments in fintech/insurtech startups [59].

Application Programming Interfaces (APIs): Interoperable software interfaces enabling seamless data integration across internal and external applications [60].

Open Insurance Ecosystem: Compliance and strategic leverage of mandated open insurance architectures for standardized data exchange [61, 27].

Generative AI: Large Language Models (LLMs) and multimodal generative tools for content generation, complex document summarization, and cognitive task augmentation [14, 62].

4.6 Dimension 6: Human Resources and Innovation Structures

Dedicated vs. Shared Teams: Structuring innovation teams as dedicated specialized units or embedded shared functions [63].

Cross-Functional X-Teams: Boundary-spanning, flexible teams combining diverse departmental skill sets and external network connections [64].

Operational-Innovation Synergy: Aligning innovation teams with core operational departments to prevent "organizational rejection" of new solutions [37].

Open Innovation Ecosystems: Systematic collaboration with universities, research centers, innovation hubs, and external partners [65, 66].

Clear Communication of Innovation Strategy: Establishing transparent communication channels to disseminate innovation goals across all hierarchy levels [33].

V. EMPIRICAL PILOT STUDY RESULTS AND STRATEGIC DISCUSSION

The empirical diagnostic instrument was pilot-tested with C-level executives and senior innovation leaders across four representative insurance companies displaying distinct structural profiles: (Company A: Major Domestic Financial Conglomerate Insurer; Company B: Subsidiary of Multinational Insurance Group; Company C: Specialized Commercial & Industrial Line Insurer; Company D: Fast-Growing Tech-Centric Insurer). [67, 68].

Table 4. Consolidated Empirical Results from Pilot Study (N = 4 Insurers)

Dimension / Critical Factor	Applicability (%)	Strategic Relevance	Adoption Maturity
1. Innovation Governance	100%	Very High (100% H/VH)	Incipient / Intermediate
• Strategy Alignment	100%	100% High / Very High	Intermediate (IT)
• Ideation & Stage-Gate	100%	100% High / Very High	Incipient (IN)
• Metrics & Targets	100%	100% High / Very High	Incipient / Intermediate
2. Organizational Culture	100%	High / Very High	Incipient / Intermediate
• Leadership Support	100%	100% Very High	Intermediate (IT)
• Risk & Failure Tolerance	100%	High (H)	Incipient (IN)
• Rewards & Incentives	100%	Medium / High	Not Used / Incipient
3. Innovation Management	100%	High / Very High	Intermediate (IT)
• Process Optimization	100%	100% Very High	Advanced (AV)
• Change Management	100%	100% High / Very High	Incipient / Intermediate
4. Risks & Compliance	100%	High (H)	Intermediate (IT)
• Sandbox Participation	75%	Medium / High	Incipient (IN)
5. Enabling Technologies	84.6%	High / Very High	Advanced / Plenary
• Cloud Computing	100%	100% Very High	Plenary (PL) [Unanimous]
• Digital Platforms	100%	100% Very High	Advanced / Plenary
• APIs & Interoperability	100%	100% Very High	Advanced / Plenary
• Drones / Telematics	50% (Line-Specific)	Medium (M)	Not Used / Incipient

Dimension / Critical Factor	Applicability (%)	Strategic Relevance	Adoption Maturity
6. Human Resources	100%	High / Very High	Intermediate (IT)
• Open Innovation	100%	100% High / Very High	Intermediate (IT)

Source: Consolidated empirical pilot research findings.

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VI. CONCLUSIONS AND RECOMMENDATIONS

6.1 Main Conclusions

This study successfully formulated, structured, and empirically validated a 34-factor conceptual framework across six dimensions for managing innovation in the Brazilian insurance market. The findings demonstrate that competitive advantage in insurance innovation transcends technology procurement; it fundamentally depends on establishing robust Innovation Governance, Organizational Culture, and Change Management capabilities to convert technological investments into long-term corporate value. The dual-scale diagnostic tool proved highly effective in pinpointing discrepancies between declared executive strategy and operational reality.

6.2 Managerial and Academic Contributions

- **For C-Level Executives & Industry Leaders:** Provides a field-tested, non-proprietary diagnostic artifact to conduct internal maturity assessments, align cross-functional leadership priorities, bridge strategic execution gaps, and guide capital allocation across digital ventures.
- **For Academic Literature:** Bridges global innovation management theories with the unique structural, economic, and regulatory realities of an emerging, highly concentrated insurance market, offering a benchmarked framework for longitudinal studies.

6.3 Limitations and Future Research Directions

Study limitations include the small pilot sample size (N = 4 insurers) and reliance on single-respondent executive perspectives per firm. Future research should pursue:

1. Large-Scale Survey Application: Administering the diagnostic instrument across a statistically representative national sample of all 58 operating insurance groups.

2. Multi-Tiered Triangulation: Capturing and cross-referencing responses from strategic (C-level), tactical (managers), and operational (specialists) tiers within each firm.

3. Comparative Segment Analysis: Investigating maturity variations between traditional incumbent conglomerates vs. digital insurtechs, as well as property/casualty vs. life/pension specialists.

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Training Needs Assessment of Barangay Secretaries: Basis for the Development of a Contextualized Capacity Enhancement Extension Program

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***Keywords*— training needs assessment, barangay secretaries, competency development, capacity building, contextualized training plan**

***Abstract*—** *This study assessed the training needs of barangay secretaries as a basis for developing a contextualized training plan responsive to their administrative responsibilities and professional development needs. Using a descriptive research design, data were collected from 53 barangay secretaries and analyzed through frequency counts, percentages, and mean scores. The assessment covered respondents' profiles, competency levels, training priorities, preferred training modalities and schedules, and challenges encountered in performing their duties. Results showed an overall competency mean of 2.58, verbally described as Competent. Digital Literacy and Office Technology ranked highest in competency, while Secretariat and Minutes Management received the lowest rating. In terms of training needs, the overall mean was 2.59, interpreted as High Priority. Official Communications and Technical Writing ranked first, followed by Digital Literacy and Office Technology and Records and Information Management. Most respondents (66.04%) preferred hands-on workshops, practicum, and simulation activities, while 81.13% favored training during weekdays within regular working hours. The most frequently reported challenge was insufficient hardware or outdated computers and software (35.85%), followed by overlapping responsibilities from auxiliary committees (33.96%). The findings highlight the importance of practical and accessible capacity-building activities that address identified training priorities and workplace challenges. The study recommends using the results as the basis for developing a contextualized training plan in coordination with concerned local government units to strengthen the competencies of barangay secretaries and support effective barangay administration.*

I. INTRODUCTION

Barangay Secretaries play an essential role in the administrative operations and delivery of public services at the barangay level. Under Section 394 of Republic Act No. 7160, otherwise known as the Local Government Code of 1991, Barangay Secretaries are responsible for maintaining records of barangay proceedings, preparing minutes of meetings, keeping official documents, and performing other administrative functions necessary for effective local governance. These responsibilities require accuracy, organization, effective communication, and adherence to established administrative and legal requirements. Their performance contributes to the transparency, accountability, and efficiency of barangay operations.

The increasing demands of local governance have further emphasized the need for continuous competency development among barangay personnel. Administrative work has become increasingly associated with digital

records management, electronic communication, information security, data privacy, and compliance with government reporting requirements. These developments have required administrative personnel to maintain appropriate knowledge and skills to perform their responsibilities effectively. Consequently, identifying competency gaps and providing relevant capacity-building interventions have become important considerations in strengthening local government administration.

In the Municipality of Talavera, Nueva Ecija, which comprises 53 barangays, Barangay Secretaries perform administrative functions that support documentation, records maintenance, official communication, and the implementation of local government programs. However, differences in educational attainment, length of service, employment status, access to technology, and previous training opportunities may influence their existing competencies and professional development needs. Without a systematic assessment of these needs, capacity-building activities may not adequately address the specific challenges encountered in the performance of their duties.

A Training Needs Assessment (TNA) provides a systematic approach to identifying the competencies required for effective job performance and determining areas where additional training may be necessary. Noe (2020) emphasized the importance of assessing training needs to establish the knowledge, skills, and abilities employees require to perform their work effectively. In the context of barangay administration, a TNA can provide an evidence-based foundation for identifying priority training areas, selecting appropriate learning modalities, and developing interventions that respond to the actual responsibilities of Barangay Secretaries.

In response to these considerations, the present study assessed the competency levels and training needs of Barangay Secretaries in the 53 barangays of Talavera, Nueva Ecija. It focused on five competency areas: Secretariat and Minutes Management; Records and Information Management; Official Communications and Technical Writing; Digital Literacy and Office Technology; and Legal and Auxiliary Functions. It also examined the respondents' profiles, preferred training modalities and schedules, and challenges encountered in performing their duties.

The study was anchored in Training Needs Assessment principles and Human Capital Theory. The former provided the basis for identifying gaps between existing competencies and the requirements of effective job performance, while the latter emphasized the value of investments in education, training, and skills development in improving individual productivity and organizational effectiveness (Becker, 1993). Republic Act No. 7160, particularly Section 394, also served as the principal legal reference for identifying the administrative responsibilities relevant to the assessment.

The findings were intended to serve as the empirical basis for developing a Contextualized Capacity Enhancement Extension Program for Barangay Secretaries in Talavera, Nueva Ecija. The proposed program was designed to address identified competency gaps through relevant capacity-building activities in administrative documentation, records management, technical writing, digital literacy, official communication, and legal documentation. By aligning extension activities with the actual needs of local government personnel, the study sought to support more responsive barangay administration and contribute to the broader goal of strengthening accountable and effective local institutions under Sustainable Development Goal 16.

Objectives of the Study

The general objective of the study was to assess the competency levels and training needs of Barangay Secretaries in the 53 barangays of Talavera, Nueva Ecija, as a basis for developing a contextualized Capacity Enhancement Extension Program.

Specifically, the study aimed to:

1. Determine the profile of Barangay Secretaries in terms of years of service, educational attainment, and employment status.
2. Assess their current competency levels in the following areas:
    - Secretariat and Minutes Management;
    - Records and Information Management;
    - Official Communications and Technical Writing;
    - Digital Literacy and Office Technology; and
    - Legal and Auxiliary Functions.
3. Identify and rank the priority training needs of Barangay Secretaries across the identified competency areas.
4. Determine their preferred training modalities and schedules for capacity-building activities.
5. Identify the challenges and barriers encountered by Barangay Secretaries in the performance of their duties.

6. Develop a Contextualized Capacity Enhancement Extension Program based on the findings of the Training Needs Assessment.

II. REVIEW OF RELATED LITERATURE

Training Needs Assessment in Public Sector Organizations

Training Needs Assessment is a systematic process of identifying discrepancies between employees' existing competencies and the knowledge, skills, and abilities required for effective job performance. It provides a basis for determining whether training is necessary and which competencies should receive priority. Rather than relying solely on assumptions about employee development needs, a systematic assessment enables organizations to identify areas requiring improvement and direct resources toward appropriate interventions.

Noe (2020) emphasized the importance of aligning training initiatives with organizational requirements and employee performance needs. This principle is particularly relevant to public sector organizations, where personnel are expected to perform specific administrative functions while complying with established policies, procedures, and service standards. For Barangay Secretaries, assessing training needs can help identify areas in which additional knowledge and practical skills may support more accurate documentation, efficient records management, and timely administrative transactions.

The literature cited in the original manuscript also emphasized the relevance of competency-based assessment in workforce development (Bandura, 2023; Madrid, 2026; Anoos, 2026; Pabelona et al., 2026). Taken together, these sources were used to support the need to base capacity-building activities on identified competency requirements and performance gaps. However, the specific findings and bibliographic details of these studies should be verified before the manuscript is submitted for publication.

In the present study, the TNA approach provided the basis for examining the competencies of Barangay Secretaries and determining priority training areas. The assessment also considered their preferred training arrangements and the challenges they experienced, allowing the proposed extension intervention to address both competency development and practical participation requirements.

Capacity Building and Local Governance

Capacity building involves strengthening the knowledge, skills, and capabilities of individuals and institutions to perform their responsibilities effectively. In local governance, capacity development supports the implementation of administrative functions, compliance with government requirements, and delivery of responsive public services. Continuous professional development is particularly important when government personnel must adapt to changing administrative procedures and technological developments.

The studies cited in the original manuscript associated capacity-building initiatives with improvements in administrative efficiency, responsiveness, accountability, and institutional performance (Patrama et al., 2025; Boufounou, 2025; Links & Draai, 2023). The manuscript also identified Philippine studies that discussed the contribution of capacity development to institutional effectiveness and community trust (Blanco, 2025; Angco, 2026).

These perspectives suggest that capacity building should be responsive to the specific responsibilities and working conditions of the personnel concerned. Training activities that are disconnected from actual job requirements may not adequately address existing competency gaps. Conversely, interventions developed from a systematic assessment can provide a clearer basis for selecting appropriate topics, learning activities, and delivery arrangements.

For Barangay Secretaries, a needs-based extension program can connect the university's community extension mandate with the administrative requirements of local government units. The present study therefore treated the TNA as a preliminary and evidence-generating step toward developing a contextualized capacity enhancement intervention for the municipality's barangay administrative personnel.

Roles and Competencies of Barangay Secretaries

The responsibilities of Barangay Secretaries are established under Section 394 of Republic Act No. 7160. These responsibilities include maintaining records of barangay proceedings, preparing and maintaining official documentation, and performing other functions necessary for barangay administration. The nature of these duties requires organizational ability, attention to detail, written communication skills, and familiarity with relevant administrative procedures.

The increasing use of digital tools and the continuing requirements for accurate documentation have expanded the practical competencies expected of administrative personnel. The original manuscript cited studies by Xu and Dai (2024) and Balaji (2025) in relation to changing competency requirements associated with digital governance, documentation standards, and

regulatory compliance. It also cited Ariñes (2025) to support the importance of identifying competency gaps among administrative personnel.

These responsibilities indicate that competency assessment should extend beyond general administrative knowledge. It should examine specific work-related tasks, including preparing meeting minutes, maintaining official records, drafting correspondence, using office applications, and understanding relevant legal and administrative requirements.

Accordingly, the present study organized the assessment into five competency areas that reflected the principal administrative functions of Barangay Secretaries. This organization provided a structured basis for examining their current competency levels and identifying the areas in which capacity-building activities might be most beneficial.

Records and Information Management

Records and information management is fundamental to transparency, accountability, institutional continuity, and administrative decision-making. Public offices rely on accurate and accessible records to document transactions, preserve organizational information, monitor activities, and provide appropriate responses to requests for information. Inadequate records management can contribute to misplaced documents, delays in retrieving information, inconsistencies in documentation, and difficulties in meeting administrative requirements.

The original manuscript cited Claude (2024) and Andini et al. (2026) in discussing the administrative consequences of inadequate records management. It also identified the transition toward electronic record-keeping as an important consideration in developing contemporary information management competencies (Thang, 2024).

The shift from exclusively paper-based documentation toward electronic files and digital records has increased the importance of skills in document organization, file naming, storage, retrieval, backup practices, and appropriate handling of information. Administrative personnel must be able to maintain records systematically while observing applicable policies governing access, confidentiality, and information security.

These considerations are relevant to Barangay Secretaries because their work involves the preparation, maintenance, and retrieval of official barangay documents. Assessing their competencies in records and information management can help identify training requirements related to both established documentation practices and the effective use of digital tools.

Digital Literacy and Electronic Governance

Digital literacy refers to the ability to use digital technologies effectively and appropriately to access, create, organize, communicate, and manage information. Within government organizations, these competencies support electronic communication, document preparation, information processing, and the implementation of digital public services.

The original manuscript cited Khan et al. (2024) in relation to the contribution of digital competencies to employee productivity and communication efficiency. It also referenced Gegana and Phahlane (2024) regarding the adoption of information and communication technologies in government service delivery. Hanelt et al. (2024) and Trenerry et al. (2021) were cited to support the importance of addressing digital competency limitations that may hinder organizational digital transformation.

For Barangay Secretaries, digital literacy may involve using word-processing and spreadsheet applications, preparing electronic reports, organizing digital files, communicating through official electronic channels, and managing information appropriately. The relevant training requirements may vary according to previous exposure to technology, available office equipment, and opportunities for professional development.

The assessment of digital literacy and office technology therefore provided an important component of the present study. Its inclusion allowed the researchers to examine the extent to which the respondents considered their existing competencies sufficient for their responsibilities and to identify areas that could be addressed through practical, context-sensitive training activities.

Official Communication and Technical Writing

Effective written communication is necessary for the preparation of official letters, memoranda, meeting minutes, reports, certifications, and other administrative documents (Holley, 2023). These documents must communicate information accurately, clearly, and appropriately while observing established formats and procedural requirements.

Technical writing skills are especially relevant to Barangay Secretaries because the documents they prepare may serve as official records of decisions, meetings, transactions, and local administrative activities. Errors in wording, formatting, or documentation may create confusion, require repeated revisions, or affect the completeness of official records.

Official communication also involves selecting appropriate language, organizing information logically, maintaining professional tone, and ensuring that

correspondence reaches the intended recipients through suitable channels. As government offices increasingly use electronic communication, written communication competencies must also be applied to digital correspondence and electronically prepared documents (Vasilieva et al., 2018).

The present study included Official Communications and Technical Writing as a distinct competency area to identify the training needs associated with preparing clear, accurate, and professionally appropriate administrative documents. This area also provided a basis for identifying possible extension activities involving document preparation, correspondence writing, report development, and practical exercises using common barangay administrative scenarios.

University Extension Programs and Local Government Partnerships

Higher education institutions contribute to community development through extension programs that transfer knowledge, develop practical skills, and respond to the needs of partner communities. Effective extension initiatives require an understanding of the target beneficiaries, their working conditions, and the challenges they encounter in applying relevant knowledge and skills.

The original manuscript cited Absolor et al. (2026) and Lee and Raschke (2020) regarding the importance of grounding extension activities in evidence and stakeholder needs. Chen et al. (2025) was also cited in connection with partnerships between educational institutions and local government units, particularly in promoting knowledge transfer, governance improvement, and community empowerment.

These perspectives support the use of a Training Needs Assessment as a basis for planning extension activities. By identifying competency gaps and training preferences before designing an intervention, an educational institution can develop activities that are more relevant to the responsibilities and practical circumstances of the intended beneficiaries.

In the context of Talavera, Nueva Ecija, the findings of the assessment were intended to guide the development of a Contextualized Capacity Enhancement Extension Program for Barangay Secretaries. The proposed program was designed to connect the administrative needs of barangays with the extension capabilities of the university through targeted and locally relevant capacity-building activities.

Synthesis and Research Gap

The reviewed literature established the importance of systematic training needs assessment, competency development, records and information management, digital literacy, effective written communication, and needs-based extension programming. Collectively, these areas highlight the relationship between employee competencies and the capacity of public institutions to perform administrative functions effectively.

The literature also suggests that capacity-building interventions should be based on identified work requirements rather than generalized assumptions about employee development needs. For Barangay Secretaries, this requires an assessment that considers their statutory responsibilities, existing competencies, preferred training arrangements, and practical challenges in performing their duties.

Although the literature cited in the original manuscript addressed public sector capacity building and the development of administrative and digital competencies, the manuscript identified a need for localized evidence concerning the specific training requirements of Barangay Secretaries in Talavera, Nueva Ecija. The extent to which their needs differed across the identified competency areas also required systematic examination.

The present study addressed this local information need by assessing Barangay Secretaries from the municipality's 53 barangays. It examined their profiles, competency levels, training priorities, preferred training modalities and schedules, and work-related challenges. The results were intended to provide a contextualized basis for developing a Capacity Enhancement Extension Program responsive to the administrative requirements of Barangay Secretaries in Talavera.

III. METHODOLOGY

Research Design

The study employed a descriptive-survey research design to assess the competency levels and training needs of Barangay Secretaries in the Municipality of Talavera, Nueva Ecija. This design was used to gather and describe information about the respondents' profiles, current competencies, training priorities, preferred learning arrangements, and challenges encountered in performing their duties.

The descriptive-survey approach was appropriate to the purpose of the study because it enabled the systematic collection of information from the target population without introducing an experimental intervention. The assessment focused on describing the existing conditions and identifying priority areas for professional development.

The findings were intended to provide an empirical basis for developing a Contextualized Capacity

Enhancement Extension Program. The study therefore emphasized the identification of competency gaps and training priorities rather than the measurement of the effectiveness of an already implemented intervention.

Research Locale and Respondents

The study was conducted in the Municipality of Talavera, Nueva Ecija, which comprised 53 barangays. The respondents were the Barangay Secretaries serving in these barangays. Total enumeration sampling was employed because the target population was manageable in size and the study sought to obtain information from the entire defined population. All 53 Barangay Secretaries were invited to participate in the assessment.

The respondents' profiles were described in terms of sex, years of service, and educational attainment. These characteristics were included to provide contextual information for understanding the respondents' backgrounds and interpreting their training needs. The final number of completed and usable questionnaires, together with the corresponding response rate, should be reported in the Results section based on the actual survey records.

Research Instrument

The primary data-gathering instrument was a Training Needs Assessment questionnaire developed and contextualized with reference to the mandated functions of Barangay Secretaries under Section 394 of Republic Act No. 7160 and relevant administrative guidelines of the Department of the Interior and Local Government. The questionnaire consisted of four parts.

Part I. Respondents' Profile. This section gathered information on the respondents' years of service, educational attainment, and sex.

Part II. Competency and Training Needs Assessment. This section examined the respondents' current competency levels and training priorities in five areas: (1) Secretariat and Minutes Management; (2) Records and Information Management; (3) Official Communications and Technical Writing; (4) Digital Literacy and Office Technology; and (5) Legal and Auxiliary Functions.

Part III. Preferred Training Modalities and Schedule. This section gathered information on the respondents' preferred arrangements for participating in capacity-building activities, including the modalities and schedules they considered suitable.

Part IV. Challenges and Barriers Encountered. This section identified the difficulties experienced by Barangay Secretaries in performing their duties. The information was intended to help contextualize their training requirements and inform the design of relevant extension activities.

The instrument used two separate four-point rating scales. The first measured current competency levels, while the second measured the priority assigned to training needs. The rating scales are provided in Tables 1 and 2 below.

Table 1. Rating Scale for Current Competency Levels

Scale	Interval	Description
4	3.25 – 4.00	Very Competent
3	2.50 – 3.24	Competent
2	1.75 – 2.49	Moderately Competent
1	1.00 – 1.74	Not Competent

Table 2. Rating Scale for Training Need Priority

Scale	Interval	Description
4	3.25 – 4.00	Urgent
3	2.50 – 3.24	High Priority
2	1.75 – 2.49	Medium Priority
1	1.00 – 1.74	Not a Priority

The two scales were interpreted separately because competency levels and training priorities represented different dimensions of the assessment. The competency scale described the respondents' perceived current capabilities, whereas the training-needs scale indicated the priority they assigned to further development.

Data-Gathering Procedure

Before data collection, permission to conduct the study was requested from the Municipal Government of Talavera and the concerned barangays. Following the necessary authorization, coordination with the Barangay Secretaries was undertaken to arrange the administration and retrieval of the questionnaires.

The questionnaires were distributed personally or administered through an agreed data-collection arrangement. The purpose of the study, the nature of participation, and the intended use of the information were explained to the respondents. Informed consent was obtained before their participation.

After the questionnaires were completed, the responses were collected and checked for completeness. The data were then encoded, organized, and prepared for statistical analysis. The resulting dataset was used to describe the respondents' profiles, assess competency levels, identify training priorities, summarize preferred training arrangements, and examine the challenges encountered in performing their duties.

The analyzed information was intended to inform the development of the proposed Contextualized Capacity Enhancement Extension Program. The program design was to be guided by the priority needs identified in the assessment, together with the practical requirements of the intended beneficiaries.

Statistical Treatment of Data

The collected data were analyzed using descriptive statistical techniques appropriate to the study's objectives. Frequency and percentage distributions were used to describe the respondents' profiles and summarize their preferred training modalities and schedules.

Weighted means were used to summarize the respondents' ratings of their current competency levels and training needs. Ranking was used to identify the competency areas and training items that received higher priority ratings.

Frequency, percentage, and ranking were used to summarize the challenges and barriers reported by the respondents, as appropriate to the format of the collected responses. The identification of competency gaps and priority interventions was guided by the results of the competency assessment and training-needs ratings.

The statistical procedures were organized according to the specific objectives of the study, as presented in Table 3.

Table 3. Statistical Treatment of Data

Research objective	Statistical treatment
Describe the respondents' profiles in terms of years of service, educational attainment, and employment status	Frequency and percentage distribution
Assess current competency levels across the five competency areas	Weighted mean
Identify and rank priority training needs	Weighted mean and ranking
Determine preferred training modalities and schedules	Frequency and percentage distribution
Identify challenges and barriers encountered in performing duties	Frequency, percentage, and ranking, as appropriate to the response format

The results of these analyses were intended to provide the basis for identifying priority competency areas and formulating appropriate capacity-building interventions for Barangay Secretaries in Talavera, Nueva Ecija. The resulting extension program was to be aligned with the identified needs, the administrative responsibilities of the respondents, and the practical conditions under which the training activities would be conducted.

IV. RESULTS AND DISCUSSION

This section presents and discusses the findings of the training needs assessment conducted among 53 barangay secretaries. The results provide an overview of the respondents' profiles and their identified training needs in relation to their administrative responsibilities and the delivery of barangay services. The findings are presented through tables and are interpreted to identify relevant areas for capacity building and professional development. The discussion serves as a basis for recommending appropriate training interventions that respond to the needs and work experiences of barangay secretaries.

Profile of the Respondents

Table 4 presents the profile of the 53 respondents in terms of years in service and highest educational attainment.

Table 4. Profile of Respondents

Profile	Frequency	Percentage
Years in Service		
Less than 1 year	3	5.66
1 to 3 years	34	64.15
4 to 6 years	3	5.66
7 years or more	13	24.52
Total	**53**	**100.00**
Highest Educational Attainment		
High School Graduate	16	30.19
College Undergraduate	18	33.96
College Graduate	19	35.85
Post-Graduate / Master's Units	0	0.00
Total	**53**	**100.00**

In terms of years in service, the majority of the respondents had been serving for 1 to 3 years, accounting for 34 respondents (64.15%). This was followed by 13 respondents (24.52%) who had been in service for 7 years or more. Meanwhile, 3 respondents (5.66%) had less than one year of service, and another 3 (5.66%) had 4 to 6 years of experience. These findings show that most respondents were in the early years of their service, while a notable proportion had longer experience in their respective roles. This mix of experience provides a valuable perspective on the training needs of barangay secretaries at different stages of their service.

In terms of highest educational attainment, 19 respondents (35.85%) were college graduates, 18 (33.96%) had completed some college education, and 16 (30.19%) were high school graduates. None reported having postgraduate qualifications or master's units. The results reflect the respondents' diverse educational backgrounds and experiences. These differences highlight the value of offering relevant and inclusive training programs that build on their existing knowledge and help them further develop the skills needed to perform their duties effectively.

In general, the profile of the respondents provides useful context for understanding their training needs. Their varied years of service and educational backgrounds underscore the importance of capacity-building activities that are practical, accessible, and responsive to their roles and responsibilities as barangay secretaries.

Competency Levels of Respondents

Table 5 presents the respondents' self-assessed competency levels across five functional areas relevant to their responsibilities as barangay secretaries. The results show a grand mean of 2.58, verbally described as Competent, indicating that the respondents generally perceived themselves as capable of performing their duties across the identified functional areas. However, the results also reveal differences in competency levels, suggesting areas where further training and skills development may be beneficial.

Table 5. Summary of Competency Levels by Functional Area

Functional Area	Capability Mean	Verbal Description	Rank
Secretariat and Minutes Management	2.05	Moderately Competent	5
Records and Information Management	3.08	Competent	2
Official Communications and Technical Writing	2.49	Competent	3
Digital Literacy and Office Technology	3.10	Competent	1
Legal and Auxiliary Functions	2.20	Moderately Competent	4
Grand Mean	**2.58 (Competent)**		

Among the five functional areas, Digital Literacy and Office Technology ranked first, with a mean of 3.10, interpreted as Competent. This was followed by Records and Information Management, which obtained a mean of 3.08, also described as Competent. These results suggest that respondents perceived themselves as relatively capable in using digital tools and managing information and records. These competencies are important in supporting the preparation of documents, organization of files, maintenance of records, and performance of routine administrative tasks.

Official Communications and Technical Writing ranked third, with a mean of 2.49, verbally described as Competent. Although the respondents generally considered themselves capable in this area, further opportunities to enhance their written communication skills may be helpful, particularly in preparing formal letters, reports, certifications, and other official documents. Strengthening these skills may contribute to clearer and more consistent communication in barangay operations.

Meanwhile, Legal and Auxiliary Functions ranked fourth, with a mean of 2.20, interpreted as Moderately Competent. Secretariat and Minutes Management ranked fifth, with a mean of 2.05, also described as Moderately Competent. These findings indicate opportunities to further develop competencies related to documenting meetings, preparing minutes, organizing proceedings, and performing other secretariat responsibilities. Additional training and practical exercises in these areas may help respondents improve their confidence and proficiency in carrying out their assigned functions.

The findings suggest that while the respondents generally perceived themselves as competent in performing their responsibilities, certain functional areas may benefit from more focused capacity-building activities. In particular, Secretariat and Minutes Management and Legal and Auxiliary Functions may be considered priorities for further training based on their relatively lower mean scores. At the same time, continuous learning in digital literacy, records management, and official communications can help sustain and further improve existing competencies. These results provide a basis for developing training interventions that build on the respondents' current capabilities while addressing areas for professional development.

Training Needs According to Priority

Table 6, on page 14, presents the training needs of the respondents across five functional areas, ranked according to their mean scores. The results yielded a grand mean of 2.59, verbally described as High Priority, indicating that the respondents generally recognized the importance of further developing their competencies through relevant training activities. The findings provide a basis for identifying areas where capacity-building initiatives may be most beneficial.

Official Communications and Technical Writing ranked first, with a mean of 2.91, followed by Digital Literacy and Office Technology, with a mean of 2.85. Both were classified as High Priority. These results highlight the value of training in preparing clear and appropriate official documents and strengthening the use of digital tools in daily administrative tasks. Activities may include writing formal letters and reports, preparing certifications, using office applications, and managing digital documents. Developing these skills may help respondents perform their responsibilities more efficiently and support effective communication and information handling within their respective barangays.

Table 6. Summary of Training Needs According to Priority

Functional Area	Training Need Mean	Verbal Description	Rank
Secretariat and Minutes Management	2.53	High Priority	4
Records and Information Management	2.62	High Priority	3
Official Communications and Technical Writing	2.91	High Priority	1
Digital Literacy and Office Technology	2.85	High Priority	2
Legal and Auxiliary Functions	2.05	Medium Priority	5
Grand Mean	**2.59 (High Priority)**		

Records and Information Management ranked third, with a mean of 2.62, also classified as High Priority. This suggests a continued need for training in organizing, storing, retrieving, and maintaining official records. Relevant activities may include systematic filing, records classification, digital recordkeeping, and the proper handling and protection of information. These competencies are important in maintaining organized records and supporting the timely retrieval of information needed for barangay operations.

Meanwhile, Secretariat and Minutes Management ranked fourth, with a mean of 2.53, and was likewise identified as a High Priority. Training in this area may focus on preparing meeting agendas, documenting proceedings, writing minutes, and organizing meeting-related records. Although this functional area ranked fourth in training priority, its relatively lower competency mean in Table 5 suggests that additional practical exercises and guided instruction may help respondents further develop their skills.

Legal and Auxiliary Functions ranked fifth, with a mean of 2.05, and was classified as Medium Priority. Although it received the lowest training need mean among the five areas, opportunities for learning may still be provided to help respondents understand relevant administrative procedures, documentary requirements, and the legal guidelines associated with their duties.

As a whole, the findings indicate that training priorities are not limited to areas where respondents may need to strengthen their competencies; they also reflect the importance they place on developing skills relevant to their daily work. Official Communications and Technical Writing, Digital Literacy and Office Technology, and Records and Information Management emerged as the leading training priorities. These areas may therefore be given greater emphasis in the design of capacity-building programs, while training in Secretariat and Minutes Management and Legal and Auxiliary Functions can complement the overall development of barangay secretaries. By aligning training activities with these identified priorities, the proposed interventions can build on existing capabilities and provide practical support for effective barangay administration.

Preferred Training Modalities

Table 7 presents the respondents' preferred training delivery modalities and schedules for extension activities. The findings provide insights into how barangay secretaries prefer to participate in capacity-building programs, which can help guide the planning and implementation of appropriate training interventions.

Table 7. Preferred Training Modalities and Schedule of the Respondents

Aspects	Category	Frequency (f)	Percentage (%)	Rank
Training Delivery Modality	Hands-on Workshop / Practicum Simulation	35	66.04	1
	Standard Lecture and Presentation	13	24.53	2
	Mentoring / One-on-One Peer Coaching	5	9.43	3
Schedule for Extension Activities	Weekdays (Within Regular Working Hours)	43	81.13	1
	Weekends (Saturdays)	10	18.87	2
	Total Respondents	**53**	**100.00**	

In terms of training delivery modality, the majority of respondents (66.04%, or 35 individuals) preferred hands-on workshops, practicum, and simulation activities, ranking this modality first. This was followed by standard lectures and presentations, preferred by 13 respondents (24.53%), while 5 respondents (9.43%) preferred mentoring or one-on-one peer coaching. The results indicate a strong preference for practical and participatory learning activities. This suggests that training programs may be more responsive to the respondents' preferences when they include demonstrations, guided exercises, and opportunities to practice tasks related to their daily responsibilities. For example, participants could practice preparing official documents, organizing records, drafting meeting minutes, and using office applications in simulated work situations. Lectures and presentations may also be incorporated to provide essential concepts and guidelines before the practical activities.

Regarding the preferred schedule for extension activities, 43 respondents (81.13%) preferred weekdays within regular working hours, while 10 respondents (18.87%) preferred weekends, particularly Saturdays. This finding suggests that most respondents favor attending training during regular working hours. Scheduling activities on weekdays may therefore be a practical option, subject to coordination with the concerned local government units and arrangements to ensure that essential barangay services remain available. At the same time, alternative schedules may be considered for participants who may have difficulty attending during regular working hours.

Overall, the results highlight the importance of considering both training methods and scheduling preferences when designing capacity-building activities for barangay secretaries. A training approach that combines hands-on exercises with concise lectures, delivered primarily on weekdays within regular working hours, may be well suited to the preferences expressed by the

respondents. Incorporating these preferences into the planning of extension activities may encourage participation and help ensure that the training is practical, accessible, and relevant to their administrative responsibilities.

Challenges and Barriers Encountered in Performing Tasks Efficiently

Table 8 presents the challenges encountered by the respondents in performing their duties efficiently. The findings identify several factors that may affect their daily administrative work, particularly the availability of appropriate technology, the distribution of responsibilities, and the availability of standardized administrative resources.

Table 8. Challenges and Barriers Encountered in Performing Task Efficiently

Challenges and Barriers	Frequency	Percentage	Rank
Lack of standardized administrative templates	14	26.42	3
Insufficient hardware / outdated computers and software	19	35.85	1
Excessive work overlap from auxiliary committees (BADAC, BCPC, BDRRMC)	18	33.96	2
Unclear communication flow or slow local feedback lines	2	3.77	4
Total	**53**	**100.00**	

The most frequently reported challenge was insufficient hardware or outdated computers and software, identified by 19 respondents (35.85%), ranking first. This finding highlights the importance of providing adequate and functional technological resources to support the administrative responsibilities of barangay secretaries. Access to reliable computers and updated software may help facilitate document preparation, records management, and other routine office tasks. Providing appropriate equipment, technical assistance, and opportunities to develop digital skills may help respondents perform these tasks more efficiently.

The second most frequently reported challenge was overlapping work from auxiliary committees, such as the Barangay Anti-Drug Abuse Council (BADAC), Barangay Council for the Protection of Children (BCPC), and Barangay Disaster Risk Reduction and Management Committee (BDRRMC). This concern was identified by 18 respondents (33.96%). The result suggests that barangay secretaries may need to manage administrative responsibilities across several functions and committees. Appropriate workload coordination, clear assignment of responsibilities, and access to administrative support may help them manage these tasks while maintaining the quality and timeliness of their work.

Meanwhile, 14 respondents (26.42%) identified the lack of standardized administrative templates, ranking third. The availability of standard templates for minutes of meetings, official letters, reports, certifications, and other documents may help promote consistency and reduce the time spent preparing routine paperwork. Developing and providing accessible templates may therefore be a practical intervention to support the respondents in carrying out their responsibilities.

Lastly, unclear communication flow or slow local feedback mechanisms was reported by 2 respondents (3.77%), ranking fourth. Although fewer respondents identified this concern, clear communication channels and timely feedback remain important in coordinating administrative activities and ensuring that documents and requests are processed appropriately.

Generally speaking, the findings indicate that the challenges encountered by barangay secretaries involve both resource-related and work-related concerns. The availability of functional computers and software emerged as the most frequently reported issue, followed by overlapping responsibilities across auxiliary committees and the lack of standardized templates. These results suggest that capacity-building initiatives may be more effective when complemented by practical support measures, such as improving access to technology, providing standardized administrative resources, and strengthening workload coordination. Addressing these concerns may help create a more supportive working environment and enable barangay secretaries to perform their responsibilities more efficiently.

V. CONCLUSIONS

Based on the findings of the training needs assessment conducted among 53 barangay secretaries, the following conclusions are drawn:

1. The respondents have varied professional backgrounds and educational attainment. Most had

been in service for 1 to 3 years, while their educational backgrounds ranged from high school graduates to college graduates. These characteristics highlight the importance of providing training opportunities that accommodate different levels of experience and learning needs.

2. The respondents generally perceived themselves as competent in performing their functions. The overall competency mean was 2.58, verbally described as Competent. Digital Literacy and Office Technology ranked highest, followed by Records and Information Management. Meanwhile, Secretariat and Minutes Management and Legal and Auxiliary Functions received lower competency ratings, indicating opportunities for further skills development.
3. The respondents identified several functional areas as high-priority training needs. Official Communications and Technical Writing ranked first, followed by Digital Literacy and Office Technology and Records and Information Management. The overall training needs mean of 2.59, described as High Priority, underscores the value of providing relevant capacity-building activities to strengthen the respondents' existing competencies.
4. Hands-on and practical learning activities are the preferred training delivery modality. Most respondents preferred workshops, practicum, and simulation activities, while the majority favored conducting extension activities on weekdays within regular working hours. These preferences provide useful guidance for designing accessible and practical training interventions.
5. The respondents encounter challenges related to technological resources and workload management. Insufficient or outdated computers and software were the most frequently reported concern, followed by overlapping responsibilities from auxiliary committees and the lack of standardized administrative templates. These findings suggest that training activities should be complemented by appropriate resources and administrative support.
6. The findings provide an empirical basis for developing a contextualized training plan for barangay secretaries. By considering the identified competency levels, training priorities, preferred learning modalities, scheduling preferences, and workplace challenges, the proposed training plan can be aligned with the respondents' actual responsibilities and professional development needs.

Recommendations

Based on the conclusions, the following recommendations are proposed:

1. Develop a contextualized training plan based on the significant findings of the study. The identified competency levels, priority training needs, preferred delivery modalities and schedules, and reported workplace challenges should serve as the primary basis for designing a training plan responsive to the actual needs of barangay secretaries. The plan should specify the training objectives, topics, activities, target participants, schedule, required resources, responsible persons, and evaluation measures.
2. Training activities should focus on preparing official letters and reports, using office applications, organizing digital and physical records, and applying appropriate records management and data protection practices. These areas received the highest training need ratings and may be addressed through practical, task-oriented sessions.
3. Workshops may cover agenda preparation, documentation of meetings, preparation of minutes, and familiarization with relevant administrative procedures and legal requirements. Practical exercises using common barangay work scenarios may help participants strengthen their skills and confidence.
4. Adopt hands-on workshops, practicum, and simulation as the primary training delivery approaches. Since most respondents preferred practical learning activities, training sessions should incorporate demonstrations, guided exercises, document preparation, and simulated administrative tasks. Lectures and presentations may be used to introduce key concepts before the practical activities.
5. Schedule training activities in consideration of the respondents' preferences and official responsibilities. Weekdays within regular working hours may be prioritized, subject to coordination with the concerned local government units and arrangements for continuity of barangay services. Alternative schedules may be considered when necessary to accommodate participants.
6. Coordinate with concerned local government units to address workplace challenges. Appropriate offices may explore opportunities to improve access to functional computers and updated

software, provide standardized administrative templates, and clarify the distribution of responsibilities across auxiliary committees. These support measures may complement the training plan and help participants apply their learning in the workplace.

7. Evaluate the effectiveness of the training plan after implementation. Evaluation may include participant feedback, practical assessments, and follow-up assessments of competency levels. The results should be used to identify improvements, determine additional learning needs, and refine future training activities.
8. Consider implementing the contextualized training plan as a community extension initiative. The university, in coordination with concerned local government units and barangay officials, may use the findings of this study to develop and implement a structured capacity-building program for barangay secretaries. Periodic reassessment of training needs is also recommended to ensure that the program remains relevant to evolving administrative responsibilities and community needs.

ETHICAL CONSIDERATIONS

The study observed ethical principles to protect the rights, dignity, privacy, and welfare of the participating barangay secretaries. Given that the respondents were public officials and employees who performed administrative functions within their respective barangays, particular attention was given to ensuring voluntary participation, confidentiality, informed consent, and protection from any potential risks associated with their involvement in the training needs assessment (TNA).

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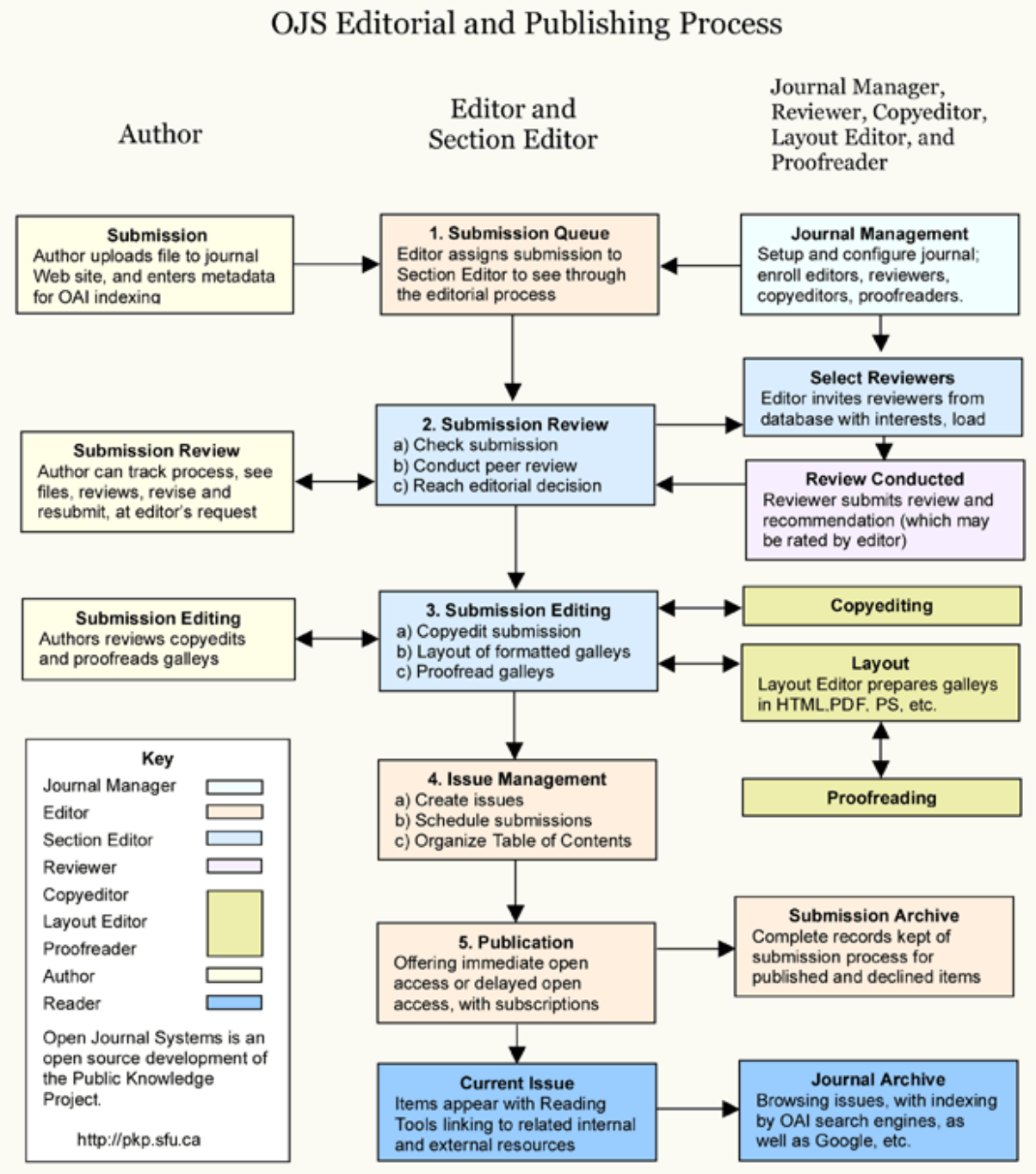

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