Assessment 2 – Research Tools and Methodologies

AI Insights from Customer Feedback: Correlating Sentiment Analysis with Business Performance in Healthcare Clinics

1 Introduction

Artificial intelligence (AI) and natural language processing (NLP) now make it possible to analyse unstructured customer feedback at scale, enabling organisations to translate raw opinions into actionable business intelligence. In the healthcare sector, however, the bridge between patient sentiment and measurable business outcomes such as revenue, retention, or referrals remains under-explored.

This project proposes an ICT-driven research framework that leverages fine-grained sentiment analysis and business-intelligence methods to examine whether emotional patterns in patient feedback can predict financial performance in clinical environments. The study builds directly on the literature gaps identified in Assessment 1 and adopts a mixed-methods design to ensure both computational accuracy and contextual validity.

2 Research Questions, Aim and Objectives

Aim To investigate the predictive relationship between AI-derived sentiment metrics and business KPIs in healthcare clinics.

Research Questions

- **RQ1:** To what extent can AI-driven sentiment analysis predict revenue in healthcare clinics?
- **RQ2:** Can fine-grained emotion classification (anger, fear, satisfaction) be reliably automated from unstructured patient feedback using NLP techniques?\
- **RQ3:** How does aspect-based sentiment analysis compare to traditional NPS as a predictor of clinic-level financial outcomes?

Objectives

1. Develop an NLP pipeline to quantify sentiment and emotion from patient-feedback text.
2. Correlate sentiment and emotional intensity with monthly revenue and NPS scores.
3. Validate AI outputs through qualitative review and ethical assessment.
4. Recommend an ICT framework linking AI insights to healthcare management decisions.

3 Comparative Analysis of Research Methodologies

Methodology	Description	Strengths	Weaknesses	Suitability
Qualitative	Explores human meaning through interviews or thematic coding.	Rich context and interpretive depth.	Limited generalisability; prone to researcher bias.	Useful to verify how patients express emotions and validate AI outputs.
Quantitative	Employs numerical measurement, hypothesis testing, and statistical inference.	Objectivity, replicability, scalability.	May overlook linguistic nuance or cultural tone.	Ideal for correlating sentiment scores with revenue (KPIs).
Mixed Methods	Integrates both qualitative and quantitative strands.	Triangulation improves validity; merges AI outputs with human interpretation.	Requires time and data integration skills.	Best suited to AI research involving both algorithms and human review.

Given that this study seeks measurable relationships between NLP-generated sentiment data (quantitative) and their contextual interpretation (qualitative), a **pragmatic mixed-methods approach** provides the most appropriate balance of rigour and flexibility. It aligns with ICT R&D practice, where prototype systems are iteratively tested and validated through empirical evidence.

4 Proposed Methodology and Research Methods

4.1 Design Paradigm

The study adopts a *pragmatic* paradigm, valuing methodological pluralism to address practical ICT challenges. Quantitative components establish statistical validity, while qualitative insights ensure interpretability and ethical robustness.

4.2 Data Collection

- **Primary Source:** Anonymised operational dataset provided by Pro-Corpo Clinics, comprising ≈ 27 000 records (2019–2024).
- **Variables:** textual feedback, NPS scores, month/year, clinic ID, and monthly revenue.
- **Data Security:** stored on encrypted drives compliant with the Australian Privacy Act (1988).

- **Authorization:** formal company consent letter ensuring confidentiality and academic use only.

The dataset originates from Pro-Corpo's post-service Net Promoter Score (NPS) program, which automatically invites clients to provide feedback within 24 hours of receiving treatment. Respondents can identify themselves or remain anonymous and answer four brief questions: (1) a 1-to-10 satisfaction rating, (2) optional comments, (3) confirmation of the store visited, and (4) optional mention of staff members for praise or concern. This process has generated approximately 27 000 records collected between 2022 and 2025, providing a rich source of structured (scores, store, month) and unstructured (text feedback) data. Monthly revenue data for each store are also available, enabling correlation between customer sentiment, NPS, and financial performance.

4.3 Data Processing Pipeline

1. Pre-processing: tokenisation, lemmatisation, and stop-word removal using SpaCy.
2. Sentiment Scoring: transformer-based model (e.g., BERT or RoBERTa) fine-tuned for healthcare language.
3. Emotion Classification: map outputs to categories—anger, fear, satisfaction—following Angelis et al. (2024).
4. Aspect Extraction: identify service features (staff, pricing, facilities) with dependency parsing.
5. Data Integration: merge monthly sentiment aggregates with revenue and NPS tables.

4.4 Quantitative Analysis

- **Descriptive Statistics:** mean sentiment per clinic, variance, and distribution trends.
- **Correlation Tests:** Pearson and Spearman coefficients to examine sentiment–revenue relationships.
- **Regression Model:** Multiple linear regression predicting revenue from sentiment and NPS.
- **Model Validation:** R^2 and p-values (< 0.05 threshold).

4.5 Qualitative Validation

A stratified sample of 200 feedback comments will be manually coded in NVivo to cross-verify model outputs. Divergences between AI predictions and human judgment will inform error analysis and bias identification.

5 Rationale for Method Choice

A purely quantitative design would capture numerical correlations but ignore linguistic subtleties such as sarcasm or emotional tone, while a purely qualitative study would lack statistical generalisability. A **mixed-methods design** therefore aligns with both AI engineering practice and ICT research methodology by combining algorithmic evaluation with human oversight. This dual approach ensures technical validity (accuracy ≥ 90%) and contextual reliability, providing a comprehensive understanding of how AI-interpreted sentiment translates into tangible business outcomes.

This study follows a correlational quantitative design complemented by qualitative validation, reflecting the mixed-methods principles described by DATAtab (2022) and Ortlieb (2021).

6 Ethical Considerations

- **Anonymity & Consent:** No personally identifiable data will be used. Pro-Corpo's written authorization ensures institutional consent.
- **Data Governance:** Compliance with the Australian Privacy Act (1988), GDPR, and HIPAA standards.
- **Bias Mitigation:** Monitor model outputs for linguistic or gender bias; retrain where disparities appear.
- **Responsible AI Design:** Outputs remain advisory, not decision-making.
- **Transparency:** All code and analysis scripts documented for audit.

Ethical approval will be sought through Torrens University's ethics process before analysis begins.

7 Data Analysis Strategies and Tools

Purpose	Tool / Technique	Output
Text processing	Python (SpaCy, Transformers)	Cleaned, vectorised text
Sentiment & Emotion Detection	Fine-tuned BERT/LLM models	Polarity + emotion scores
Statistical Analysis	Pandas, SciPy, SPSS (optional)	Correlation and regression results
Qualitative Coding	NVivo or manual thematic analysis	Verified emotion themes
Visualisation	Matplotlib, Power BI dashboards	Trend plots and correlation heatmaps
Triangulation	Combine AI, NPS and revenue metrics	Composite predictive model

Data will be visualised as scatterplots and heatmaps linking sentiment polarity to revenue trends. The mixed-methods output will reveal whether specific emotional tones (e.g., satisfaction vs anger) predict measurable changes in clinic income or retention.

8 Limitations and Delimitations

- **Scope:** Restricted to one clinic group (Pro-Corpo), limiting cross-industry generalisability.
- **Data Bias:** Feedback may be skewed toward extreme experiences.
- **Technical Constraints:** Transformer models require substantial GPU resources; cloud compute costs may constrain retraining.
- **Time Frame:** Analysis limited to 2022–2022 data.
- **Delimitation:** Study focuses on correlational evidence, not causal inference.

9 Conclusion

This research framework establishes how AI-driven sentiment analysis can extend beyond descriptive analytics to predictive business intelligence in healthcare. By combining quantitative correlation modelling with qualitative verification, the study aligns technical AI development with managerial relevance and ethical governance.
The mixed-methods approach reflects ICT R&D principles—iterative experimentation, data integration, and responsible innovation—and sets the foundation for future prototypes that integrate feedback analytics directly into clinical decision-support dashboards.

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