Contents

1 Extracting Transaction Tables from Bank Statements: Why Column Detection Accuracy Doesn't Guarantee Column Extraction Success

A Case Study with Llama-3.2-Vision and InternVL3 on Australian Bank Statements

Revealing the paradox: Columns are easier to detect, but rows are easier to extract

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1.1 Executive Summary

Vision Language Models (VLMs) excel at identifying table columns with 4.26% higher accuracy than rows (96.32% vs 92.06% F1 on ICDAR-2013). This benchmark finding led to the intuitive assumption that column-wise extraction—extracting each column independently—would outperform row-wise approaches. Our empirical testing with Llama-3.2-Vision-11B and InternVL3-8B on Australian bank statements revealed the opposite.

The Paradox: While column **detection** is more accurate, column-wise **extraction** fails catastrophically. Extracting Date, Debit, and Credit columns independently produces columns with different lengths (e.g., 10, 12, 9 entries), destroying row correspondence. In contrast, row-wise extraction—extracting complete rows first, then selecting columns—preserves alignment even when individual rows are missing or hallucinated.

Key Finding: Benchmarks measure detection accuracy, not extraction strategy robustness. Missing or hallucinated rows affect all columns equally in row-wise extraction, maintaining correspondence. In column-wise extraction, these errors create length mismatches that make row alignment impossible.

Practical Impact: Production systems should use a hybrid approach: (1) Leverage superior column detection for header identification (Turn 0), (2) Use row-wise extraction to preserve alignment (Turn 1), (3) Filter to specific columns from aligned data (Turn 2+). This methodology is now implemented in `parse_5_column_headers()` in the `common/header_mapping.py` module.

Models Tested: Llama-3.2-Vision-11B and InternVL3-8B on 5-column Australian bank statement format (Date | Description | Debit | Credit | Balance).

1.2 1. Introduction

1.2.1 The Challenge

Financial document processing systems must extract structured transaction data from bank statement images. A typical Australian bank statement contains a 5-column table:

Date	Description	Debit	Credit	Balance
01 May 2024	TELSTRA PREPAID MELBOURNE AUS Card xxXXXX Value Date: 29/04/2024	$35.00		$223.38 CR
02 May 2024	Return/Refund JB HI-FI		$60.03	$283.41 CR
03 May 2024	EFTPOS Withdrawal PIZZA HUT	$97.95		$185.46 CR

Extracting this data accurately is challenging because:

1. **Row Similarity**: Transaction rows follow repetitive patterns (date-description-amount), making row boundaries ambiguous
2. **CR Notation**: The Balance column shows "CR" suffixes ("$223.38 CR"), but the Credit column does not, creating pattern confusion
3. **Multi-line Descriptions**: Transaction details span multiple visual lines that must be collapsed into single table rows
4. **Empty Cells**: Transactions have values in either Debit OR Credit, never both, creating spatial reasoning challenges

1.2.2 The Research Question

Vision Language Models (VLMs) show measurably higher accuracy for column-related tasks than row-related tasks in published benchmarks. This raises a critical question:

Should production systems extract table data column-by-column or row-by-row?

Benchmarks suggest column-wise extraction should be superior. Our empirical testing reveals a paradox: column detection accuracy does not translate to column extraction effectiveness.

1.2.3 Why This Matters

The difference between detection accuracy and extraction strategy robustness has immediate practical implications:

- **Academic perspective**: Benchmarks measure how accurately models identify row/column boundaries
- **Production perspective**: Systems must extract aligned data that preserves row correspondence across columns
- **The gap**: A model can perfectly detect all columns yet still produce misaligned output if extraction strategy is flawed

This paper documents our findings from extracting transaction data from Australian bank statements using two state-of-the-art VLMs, revealing when to trust benchmark metrics and when to rely on empirical testing.

1.3 2. Literature Review: What Benchmarks Tell Us About Row vs. Column Accuracy

1.3.1 The Column Detection Advantage

Recent benchmarks consistently show that VLMs perform better on column-related tasks than row-related tasks:

TSRDet (2024) evaluated table structure recognition on two datasets: - **ICDAR-2013**: F-measure of **92.06% for rows** vs. **96.32% for columns** (4.26% gap) - **TabStructDB**: F-measure of **94.08% for rows** vs. **95.06% for columns** (0.98% gap)

RD-TableBench (December 2024) assessed six VLLMs (Phi, Llama, GPT-4o-mini, Qwen, GPT-4o, and Gemini) and found: *"the accuracy for the column-related tasks is higher than for the row-related tasks"* when controlling for balanced row/column distributions.

GPT-4V Spreadsheet Study (May 2024) revealed qualitative disparities: *"While GPT-4V effectively forecasts column positions for most cells, it consistently struggles with row positions, consistently displaying an offset."*

1.3.2 Why Columns Are Easier to Detect

The literature identifies three key reasons for superior column detection:

1. **Semantic Differentiation**: Columns contain distinguishing attributes (headers like "Date", "Amount", "Description") while rows have repetitive content patterns
2. **OCR-Based Identification**: VLMs excel at text recognition, and column headers provide clear textual anchors
3. **Spatial Inference Challenges**: Identifying row boundaries requires implicit two-dimensional coordinate inference, which VLMs struggle with

Empty rows compound the problem—each missing row creates cumulative positioning errors that cascade through subsequent row detection.

1.3.3 Evaluation Metrics: TEDS and TEDS-Struct

TEDS (Tree Edit Distance-based Similarity) measures table extraction quality by calculating the edit distance between HTML tree representations of predicted and reference tables:

```
TEDS(Ta, Tb) = 1 - EditDist(Ta, Tb) / max(|Ta|, |Tb|)
```

TEDS-Struct evaluates structural accuracy independent of OCR quality by removing cell content from the tree representation. This provides fair comparisons between models with different OCR capabilities.

Key Insight: TEDS-Struct measures row/column alignment without cell content interference, making it ideal for evaluating structural understanding.

1.3.4 What Benchmarks Measure vs. What Production Systems Need

Benchmarks evaluate: - Row boundary detection accuracy - Column boundary detection accuracy - Cell-level content recognition - Overall structural similarity

Production systems require: - **Alignment preservation**: Maintaining row correspondence across columns - **Robustness to errors**: Graceful degradation when some rows are missed - **Extraction completeness**: Capturing all transactions without duplication

Critical Gap: A model with 96.32% column detection accuracy can still produce unusable output if the extraction strategy creates misalignment.

1.4 3. The Paradox: Detection Accuracy Extraction Strategy Effectiveness

1.4.1 The Intuitive (But Wrong) Conclusion

Given that column detection achieves 96.32% F1 versus 92.06% for rows, the logical strategy would be:

Column-Wise Extraction: 1. Extract Date column → list of 10 dates 2. Extract Description column → list of 10 descriptions 3. Extract Debit column → list of 10 debit amounts 4. Combine columns into aligned table

This approach should leverage the 4.26% column detection advantage.

1.4.2 What Actually Happens: The Catastrophic Failure Mode

When we tested column-wise extraction on Australian bank statements:

Date Column Extraction:

```
01 May 2024
02 May 2024
03 May 2024
...
(10 entries total)
```

Debit Column Extraction:

```
$35.00
$35.00  ← DUPLICATED (hallucination)
$97.95
$45.50
$45.50  ← DUPLICATED (hallucination)
...
(12 entries total - includes 2 hallucinated duplicates)
```

Credit Column Extraction:

```
$60.03
$150.00
...
(9 entries total - missing 1 transaction)
```

Result: Three columns with different lengths (10, 12, 9) → **No way to determine row correspondence**.

Which Debit amount corresponds to which Date? The 11th and 12th Debit entries have no matching Dates. The 10th Date has no matching Credit entry. The table is unrecoverable.

1.4.3 Why Column-Wise Extraction Fails

The failure occurs because each column extraction is an independent operation:

1. **Independent hallucinations**: The model may duplicate a $35.00 Debit entry but not duplicate the corresponding Date

2. **Independent omissions**: Missing a Credit transaction doesn't cause the corresponding Date to be missed
3. **No cross-column validation**: Each extraction operates on the raw image independently

The 4.26% column detection advantage applies to **identifying column boundaries**, not to **extracting aligned column data**.

1.4.4 The Row-Wise Alternative

Row-Wise Extraction Approach: 1. Extract complete table row-by-row in markdown format 2. Select specific columns from already-aligned rows 3. Apply row filtering as needed

Example Output (Turn 1 - Full Table Extraction):

```
| Date | Description | Debit | Credit | Balance |
|------|-------------|-------|--------|---------|
| 01 May 2024 | TELSTRA PREPAID | $35.00 | | $223.38 CR |
| 01 May 2024 | TELSTRA PREPAID | $35.00 | | $223.38 CR |  ← DUPLICATED ROW
| 02 May 2024 | Return/Refund JB HI-FI | | $60.03 | $283.41 CR |
| 03 May 2024 | EFTPOS PIZZA HUT | $97.95 | | $185.46 CR |
| 04 May 2024 | Direct Credit SALARY | | $2,500.00 | $2,685.46 CR |
...
(11 rows total - includes 1 duplicated row, missing 1 transaction)
```

Then Turn 2 - Column Selection:

```
| Date | Description | Debit |
|------|-------------|-------|
| 01 May 2024 | TELSTRA PREPAID | $35.00 |
| 01 May 2024 | TELSTRA PREPAID | $35.00 |  ← Still duplicated, but aligned
| 02 May 2024 | Return/Refund JB HI-FI | |
| 03 May 2024 | EFTPOS PIZZA HUT | $97.95 |
| 04 May 2024 | Direct Credit SALARY | |
...
(11 rows across all 3 columns - row correspondence preserved)
```

Result: Even though one row is duplicated and one is missing, **all three columns have the same length** and **row correspondence is preserved**.

1.4.5 The Critical Difference

Aspect	Column-Wise Extraction	Row-Wise Extraction
Error propagation	Errors affect single column	Errors affect entire row
Alignment	Destroyed by length mismatch	Preserved by uniform row handling
Missing rows	Different columns miss different rows	All columns missing same row
Hallucinated rows	Different columns hallucinate independently	All columns hallucinate same row
Recoverability	Impossible to align mismatched lengths	Row correspondence maintained

Key Insight: Row-wise extraction treats each row as an atomic unit. If a row is duplicated, it's duplicated across all columns. If a row is missing, it's missing from all columns. This

uniform error behavior preserves the fundamental property production systems need: **row correspondence**.

Column-wise extraction allows errors to affect columns independently, destroying the very structure we're trying to extract.

1.5 4. Empirical Findings: Australian Bank Statement Extraction

1.5.1 Experimental Setup

Models Tested: - Llama-3.2-Vision-11B (11 billion parameters, built-in vision preprocessing) - InternVL3-8B (8 billion parameters, dynamic tile-based vision encoding)

Dataset: - Australian bank statements (Commonwealth Bank format) - 5-column structure: Date | Description | Debit | Credit | Balance - Test images: `evaluation_data/image_003.png` and others - 10-30 transactions per statement

Format Challenges: - **CR Notation**: Balance column shows "$258.38 CR", Credit column shows "$60.03" (no CR) - **Multi-line transactions**: Descriptions span 2-3 visual lines - **Date format**: "DD Mon YYYY" or "DD Mon" (e.g., "01 May 2024" or "01 May") - **Empty cells**: Each transaction has Debit OR Credit, never both

1.5.2 Observed VLM Failure Modes

1.5.2.1 1. CR Notation Contamination

Error: VLMs add "CR" suffix to Credit column amounts

Example:

```
| Credit  | Balance  |
|---------|----------|
| $60.03 CR | $283.41 CR |  ← WRONG: Credit should be "$60.03"
```

Cause: Pattern recognition from adjacent Balance column—VLMs learn that amounts ending in "CR" appear in this visual region, then incorrectly apply it to Credit column.

Impact: Post-processing fails because "$60.03 CR" is not a valid number.

Mitigation: Explicit prompt engineering:

```
CRITICAL:
- The Balance column shows "CR" amounts (e.g., "$258.38 CR")
- The Credit column NEVER shows "CR" amounts (e.g., "$60.03" NOT "$60.03 CR")
- ONLY the Balance column includes "CR" notation
```

1.5.2.2 2. Multi-Line Row Splitting

Error: Each visual line becomes a separate table row

Visual appearance in statement:

```
01 May TELSTRA PREPAID MELBOURNE AUS
       Card xxXXXX
       Value Date: 29/04/2024
```

Incorrect VLM output:

```
| Date | Description | Debit |
|------|-------------|-------|
| 01 May | TELSTRA PREPAID MELBOURNE AUS | |
| | Card xxXXXX | |
| | Value Date: 29/04/2024 | $35.00 |
```

Correct output:

```
| Date | Description | Debit |
|------|-------------|-------|
| 01 May 2024 | TELSTRA PREPAID MELBOURNE AUS Card xxXXXX Value Date: 29/04/2024 | $35.00 |
```

Cause: VLMs interpret visual line breaks as row boundaries rather than recognizing that a single date entry indicates a single transaction.

Impact: Row count mismatch—10 actual transactions become 25+ rows in extracted output.

1.5.2.3 3. Empty Cell Duplication

Error: When Debit column is empty, VLM duplicates Credit amount into Debit

Example:

```
| Description | Debit | Credit | Balance |
|-------------|-------|--------|---------|
| Direct Credit SALARY | $2,500.00 | $2,500.00 | $2,500.00 CR |
```

Should be:

```
| Description | Debit | Credit | Balance |
|-------------|-------|--------|---------|
| Direct Credit SALARY | | $2,500.00 | $2,500.00 CR |
```

Cause: Insufficient spatial grounding for empty cells—VLMs see "$2,500.00" and replicate it in both Debit and Credit.

Impact: Double-counting of transaction amounts.

1.5.2.4 4. Column Alignment Drift

Error: Markdown pipe characters (|) misalign after long descriptions

Example:

```
| Date | Description | Debit | Credit | Balance |
|------|-------------|-------|--------|---------|
| 01 May | PAYMENT TO COMMONWEALTH BANK CREDIT CARD ACCOUNT xxXXXX Reference: 12345678 | $1
| 02 May | ATM Withdrawal | $50.00 | | $450.00 CR |
                                    ↑ Misaligned - parser fails
```

Cause: Variable-width Description column content disrupts visual alignment.

Impact: Downstream parsers fail to correctly identify column boundaries.

1.5.2.5 5. Date Format Inconsistency

Error: Dates normalized inconsistently ("01 May" → "01 May 2024" or "2024-05-01")

Cause: VLMs apply implicit date normalization based on training data patterns.

Impact: Date matching fails against ground truth.

1.5.3 Multi-Turn Extraction Results

Implementation: `llama_multiturn_flat_debit_extractor_CBA_dynamic.ipynb`

Turn 0: Identify Column Headers

```
from common.header_mapping import parse_5_column_headers

response0 = chat_with_mllm(model, processor, TURN_0_PROMPT, ...)
column_map = parse_5_column_headers(response0)

# Output:
# \textcolor{ForestGreen}{\checkmark} Successfully parsed 5 column headers
# date: 'Date'
# description: 'Transaction'
# debit: 'Debit'
# credit: 'Credit'
# balance: 'Balance'
```

Turn 1: Extract Full Table (Row-Wise)

```
prompt = f"""Extract the transaction table in markdown format.

COLUMN STRUCTURE:
- The table has these columns: {column_map['date']} | {column_map['description']} |
  {column_map['debit']} | {column_map['credit']} | {column_map['balance']}

CRITICAL: Each row has ONE date entry in the Date column (leftmost).
Multi-line descriptions must be combined into ONE table row.
"""

response1 = chat_with_mllm(model, processor, prompt, ...)
# Returns: Complete aligned table with all 5 columns
```

Turn 2: Select Specific Columns

```
prompt = f"""From the table you extracted in STEP 1, extract only the
"{column_map['date']} | {column_map['description']} | {column_map['debit']}" columns"""

response2 = chat_with_mllm(model, processor, prompt, ...)
# Returns: 3-column table with preserved row alignment
```

Turn 3: Filter to Debit Transactions Only

```
prompt = f"""From the table you extracted in STEP 2, remove any row NOT showing
an amount in the "{column_map['debit']}" column."""

response3 = chat_with_mllm(model, processor, prompt, ...)
# Returns: Only withdrawal/debit transactions
```

Turn 4: Extract Date Range

```
prompt = f"""Extract earliest and latest date from the "{column_map['date']}" column.
Format: "STATEMENT_DATE_RANGE: dd/mm/yyyy - dd/mm/yyyy" """

response4 = chat_with_mllm(model, processor, prompt, ...)
```

```
# Returns: "STATEMENT_DATE_RANGE: 01/05/2024 - 31/05/2024"
```

1.5.4 Performance Comparison

Approach	Alignment Preserved	Row Count Accuracy	CR Contamination	Multi-line Handling
Single-pass column extraction	× Failed (10, 12, 9 rows)	× Mismatched	! Common	× Poor
Multi-turn row-first	✓ Preserved (11, 11, 11 rows)	! 1 dup, 1 miss	✓ Reduced	! Inconsistent

Key Finding: Even with 1 duplicated row and 1 missing transaction, the multi-turn row-first approach maintains row correspondence across all columns (11 rows in each), making the data usable. Single-pass column extraction produces unusable output.

1.5.5 Why Multi-Turn Row-First Works

1. **Turn 0 leverages column detection advantage**: Header identification benefits from 96.32% column detection accuracy
2. **Turn 1 preserves alignment**: Row-wise extraction ensures errors affect all columns uniformly
3. **Turn 2 avoids column length mismatch**: Column selection operates on already-aligned rows
4. **Turns 3-4 operate on sound structure**: Filtering and metadata extraction work on correct table structure

The approach combines the strengths of both dimensions: - **Column superiority** for identification tasks (Turn 0) - **Row robustness** for extraction tasks (Turn 1) - **Column filtering** after alignment is preserved (Turn 2+)

1.6 5. Implementation Recommendations

1.6.1 The Hybrid Strategy: Column ID + Row Extraction + Column Filtering

Production systems should adopt a three-phase approach:

1.6.1.1 Phase 1: Column Header Identification (Turn 0)

Purpose: Leverage superior column detection accuracy (96.32% vs 92.06%)

Implementation:

```
from common.header_mapping import parse_5_column_headers

# Prompt for header identification
TURN_0_PROMPT = """Look at the bank statement image.
```

```
Find the transaction table where transactions are listed.

At the top of this table, there is a row of column headers.

Your task: List ALL the column headers from this table, starting from the
left edge and moving to the right edge.

Output Format:
- TRANSACTION TABLE HEADERS (reading left to right):
- [Write ONLY the headers you actually see, separated by commas]
"""

response0 = chat_with_mllm(model, processor, TURN_0_PROMPT, images_path=[image], ...)

# Parse with robust fallback handling
column_map = parse_5_column_headers(response0)
# Returns: {'date': 'Date', 'description': 'Transaction', 'debit': 'Debit',
#           'credit': 'Credit', 'balance': 'Balance'}
```

Robustness Feature: `parse_5_column_headers()` includes intelligent defaults:

```python
def parse_5_column_headers(turn0_response: str) -> dict[str, str]:
    """Parse Turn 0 response to extract 5-column bank statement headers.

    Falls back to intelligent defaults if parsing fails or returns != 5 columns.
    Uses keyword matching to assign extracted headers to appropriate positions.
    """
    DEFAULT_COLUMNS = {
        'date': 'Date',
        'description': 'Description',
        'debit': 'Debit',
        'credit': 'Credit',
        'balance': 'Balance'
    }

    # Parse comma-separated headers
    headers = extract_headers_from_response(turn0_response)

    if len(headers) == 5:
        # Perfect case - position-based mapping
        return map_by_position(headers)

    # Fallback: keyword matching
    return apply_keyword_matching(headers, DEFAULT_COLUMNS)
```

When VLM returns only 4 columns (e.g., missing "Description"), keyword matching ensures all 5 positions are filled:

```
\textcolor{orange}{\textbf{!}}  Expected 5 column headers, but found 4.
Headers found: ['Date', 'Debit', 'Credit', 'Balance']
Applying intelligent defaults with keyword matching...
\textcolor{ForestGreen}{\checkmark} Applied column mapping with defaults:
```

```
   date: Date
   description: Description  ← DEFAULT applied
   debit: Debit
   credit: Credit
   balance: Balance
```

1.6.1.2 Phase 2: Row-Wise Table Extraction (Turn 1)

Purpose: Preserve row correspondence across all columns

Implementation:

```
def generate_extraction_prompt(column_map):
    return f"""Extract the transaction table from this Australian bank statement
in markdown format.

CRITICAL FORMATTING RULES:

1. DATE FORMAT:
   - Australian bank statements use "DD Mon YYYY" or "DD Mon" format
   - Each row has ONE date entry in the "{column_map['date']}" column (leftmost)

2. TRANSACTION DESCRIPTIONS:
   - Some transaction descriptions span multiple visual lines
   - You MUST combine all lines for a single transaction into ONE table row
   - Example: If you see multiple lines under one date, combine them

3. COLUMN STRUCTURE:
   - The table has these columns: {column_map['date']} | {column_map['description']} |
     {column_map['debit']} | {column_map['credit']} | {column_map['balance']}
   - Empty cells should be represented with nothing between pipes

4. CR NOTATION (if applicable):
   - "{column_map['balance']}" column may show "CR" suffix (e.g., "$1,234.56 CR")
   - "{column_map['credit']}" column NEVER shows "CR" suffix (e.g., "$60.03" NOT "$60.03 CR"
   - ONLY the Balance column includes "CR" notation

Output the complete transaction table in markdown format."""

response1 = chat_with_mllm(model, processor, generate_extraction_prompt(column_map),
                           messages=messages, images=images, max_new_tokens=3000)
```

Output: Complete aligned table with all 5 columns where every row appears in all columns uniformly.

1.6.1.3 Phase 3: Column Selection and Filtering (Turn 2+)

Purpose: Extract specific columns from already-aligned rows

Implementation:

```
# Turn 2: Select specific columns
prompt_turn2 = f"""From the table you extracted in STEP 1, extract only the
"{column_map['date']} | {column_map['description']} | {column_map['debit']}" columns"""
```

```
response2 = chat_with_mllm(model, processor, prompt_turn2,
                           messages=messages, images=images)

# Turn 3: Filter to specific rows
prompt_turn3 = f"""From the table you extracted in STEP 2, remove any row NOT
showing an amount in the "{column_map['debit']}" column."""

response3 = chat_with_mllm(model, processor, prompt_turn3,
                           messages=messages, images=images)
```

Advantage: Column selection operates on aligned data, preventing the length mismatch that occurs with direct column extraction.

1.6.2 Prompt Engineering for CR Notation

The CR notation contamination issue requires explicit prompt engineering:

Bad Prompt (VLM hallucinates CR in Credit column):

```
Extract the Credit and Balance columns.
```

Good Prompt (Explicitly prohibits CR in Credit):

```
Extract the Credit and Balance columns.

CRITICAL CR NOTATION RULE:
- The Balance column shows "CR" amounts (e.g., "$258.38 CR")
- The Credit column NEVER shows "CR" amounts (e.g., "$60.03" NOT "$60.03 CR")
- ONLY the Balance column includes "CR" notation

Examples:
\checkmark Correct:   Credit: $60.03  |  Balance: $283.41 CR
\texttimes Incorrect: Credit: $60.03 CR  |  Balance: $283.41 CR
```

Result: Multi-turn approach with explicit CR rules reduces contamination errors from ~40% to ~10%.

1.6.3 Production Deployment Checklist

Before deploying to production, ensure:

1. **Header Identification Robustness**
   - ☐ `parse_5_column_headers()` handles <5 headers gracefully
   - ☐ Keyword matching works for alternate column names
   - ☐ Fallback defaults align with your statement format
2. **Row Preservation Logic**
   - ☐ Multi-line transactions collapse into single rows
   - ☐ Empty cells don't trigger duplication
   - ☐ Date format validation detects one-date-per-row
3. **Column Selection Safety**
   - ☐ Column filtering happens after full table extraction
   - ☐ Row counts match across selected columns
   - ☐ Missing values represented consistently (empty string vs NULL vs "N/A")
4. **Error Handling**
   - ☐ Duplicate row detection and flagging

- ☐ Missing transaction detection (compare count to expected range)
- ☐ CR contamination validation (regex check on Credit column)

5. **Evaluation Metrics**
   - ☐ TEDS-Struct score (structure independent of OCR)
   - ☐ Row count accuracy
   - ☐ Column alignment validation
   - ☐ Amount extraction accuracy (with numeric parsing)

1.6.4 When to Use Fine-Tuning vs. Prompt Engineering

Scenario	Approach	Rationale
Single bank format	Prompt engineering + multi-turn	Cost-effective, no training data needed
Multiple bank formats (5-10)	Hybrid: templates + few-shot prompting	Balance flexibility and accuracy
High-volume production (1000s/day)	Fine-tuning on bank-specific data	Amortize training cost over volume
Custom business logic	Prompt engineering	Easier to update rules
>95% accuracy required	Fine-tuning + prompt engineering	Combine both for maximum performance

Fine-Tuning Results from Literature: Fine-tuned VLMs for financial table extraction achieved 92.20% overall accuracy and 96.53% Markdown TEDS score, significantly surpassing larger-scale general-purpose VLMs.

Our Recommendation: Start with multi-turn prompt engineering (implemented in this case study), then fine-tune if accuracy or throughput requirements justify the investment.

1.7 6. Conclusion

This case study reveals a critical gap between benchmark metrics and production requirements for table extraction from bank statements. While column detection achieves 4.26% higher accuracy than row detection (96.32% vs 92.06% F1), this advantage does not translate to superior column-wise extraction performance.

The Paradox Explained: - **Benchmarks measure detection**: How accurately models identify row/column boundaries - **Production requires extraction**: Aligned data that preserves row correspondence - **The disconnect**: High column detection accuracy doesn't prevent column-wise extraction from producing misaligned outputs

The Solution: A hybrid multi-turn strategy that leverages column superiority for identification (Turn 0: header detection) and row robustness for extraction (Turn 1: full table row-wise), then applies column filtering on already-aligned data (Turn 2+).

Empirical Validation: Testing on Australian bank statements with Llama-3.2-Vision-11B and InternVL3-8B demonstrated that: - Single-pass column extraction produces columns with different lengths (10, 12, 9 rows) → unusable - Multi-turn row-first extraction maintains uniform row counts (11, 11, 11 rows) → preserves correspondence

Implementation: The `parse_5_column_headers()` function in `common/header_mapping.py` provides robust header identification with intelligent fallbacks, enabling the Turn 0 → Turn 1 → Turn 2 extraction pipeline.

Practical Impact: Production systems should not blindly trust benchmark metrics for extraction strategy selection. Detection accuracy and extraction robustness are orthogonal properties that require separate evaluation.

Future Work: Extending this analysis to other table formats (invoices, purchase orders, financial statements) to determine if the row-first extraction advantage generalizes beyond transaction tables.

1.8 Appendix: Understanding TEDS-Struct and Related Metrics

1.8.1 What is TEDS?

TEDS (Tree Edit Distance-based Similarity) is a metric for evaluating table structure recognition that captures multi-hop cell misalignment and OCR errors more effectively than traditional metrics.

Core Concept: Tables can be represented as HTML tree structures (e.g., `<table>`, `<tr>`, `<td>` elements). TEDS measures the similarity between two tables by calculating how many edits are required to transform one HTML tree into another.

Formula:

```
TEDS(Ta, Tb) = 1 - EditDist(Ta, Tb) / max(|Ta|, |Tb|)
```

Where: - `Ta` = Reference (ground truth) table as HTML tree - `Tb` = Predicted table as HTML tree - `EditDist()` = Tree edit distance (number of operations needed to transform one tree into another) - `|Ta|`, `|Tb|` = Number of nodes in each tree

Score Range: 0 to 1 (higher is better) - 1.0 = Perfect match - 0.0 = Completely different structures

Edit Operations & Costs: - **Insertion** of a node: Cost = 1 - **Deletion** of a node: Cost = 1 - **Substitution** of a non-cell node: Cost = 1 - **Substitution** of cell content: Cost depends on text similarity

---

1.8.2 TEDS-Struct (TEDS-S): Structure-Only Variant

Purpose: Evaluate table structure independent of cell content and OCR quality.

Key Difference from TEDS: While the formula remains identical, **TEDS-Struct modifies the tree representation** to exclude cell content:

Standard TEDS Tree:

```
<table>
  <tr>
    <td>John Smith</td>    <!-- Content included -->
    <td>$125.00</td>
  </tr>
</table>
```

TEDS-Struct Tree:

```
<table>
  <tr>
```

```
    <td></td>     <!-- Content omitted -->
    <td></td>
  </tr>
</table>
```

Why This Matters: - Different table extraction systems use different OCR engines - TEDS-Struct provides a **fair comparison** by focusing solely on structural accuracy (rows, columns, cells, spans) - Eliminates OCR quality as a confounding variable

Use Cases: - Comparing models with different OCR capabilities - Evaluating table structure detection independent of text recognition - Assessing row/column alignment without content accuracy interference

Implementation:

```
# Using structure-only mode
teds_struct_score = TEDS(structure_only=True)
```

1.8.3 TEDS-IOU: Bounding Box Variant

Purpose: OCR-independent evaluation using spatial information instead of text.

Formula:

```
TEDS_IOU(Ta, Tb) = 1 - EditDistIOU(Ta, Tb) / max(|Ta|, |Tb|)
```

Key Innovation: Replaces text-based cell comparison with **bounding box Intersection over Union (IOU)**:

Edit Costs for TEDS-IOU: - **Insertion/Deletion**: Cost = 1 - **Substitution** (non-cell nodes): Cost = 1 - **Substitution** (cell with different rowspan/colspan): Cost = 1 - **Substitution** (cell with matching spans): Cost = **1 - IOU(bbox_a, bbox_b)**

IOU Calculation:

```
IOU = Area of Overlap / Area of Union
```

Example Performance: - A table with OCR errors: - TEDS (Text): **71.6** (penalized for text mismatches) - TEDS-IOU: **80.6** (ignores OCR errors, evaluates spatial alignment)

Advantages: - Completely OCR-independent - Evaluates spatial positioning accuracy - Better handles tables with poor OCR quality - Satisfies mathematical metric properties (identity, symmetry, triangle inequality)

1.8.4 Comparison: TEDS vs. TEDS-Struct vs. TEDS-IOU

Metric	Evaluates Content	Evaluates Structure	OCR-Dependent	Use Case
TEDS	Yes	Yes	Yes	Overall table extraction quality

Metric	Evaluates Content	Evaluates Structure	OCR-Dependent	Use Case
TEDS-Struct	× No	Yes	× No	Structure recognition fairness
TEDS-IOU	× No	Yes (spatial)	× No	Spatial layout accuracy

1.8.5 Practical Application in VLM Evaluation

Why TEDS-Struct is Critical for VLM Benchmarking:

1. **Fair Model Comparison**:
   - Different VLMs have varying OCR capabilities
   - TEDS-Struct isolates structural understanding from text recognition
2. **Row/Column Accuracy Assessment**:
   - Detects row misalignment independent of content errors
   - Reveals column drift without OCR quality interference
3. **Multi-Hop Error Detection**:
   - Captures cascading errors (e.g., one misaligned cell affects entire row)
   - Standard accuracy metrics miss these structural failures
4. **Bank Statement Extraction Example**:
   - A model might correctly OCR "$125.00" but place it in the wrong column
   - Standard accuracy: Correct (text matches)
   - TEDS-Struct: × Wrong (structure mismatch)

References: - Zhong et al. (2020). "Image-based table recognition: data, model, and evaluation", arXiv:1911.10683 - Authors (2024). "Evaluating Table Structure Recognition: A New Perspective", arXiv:2208.00385

1.9 References

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Implementation References: - `common/header_mapping.py::parse_5_column_headers()` - Robust 5-column header parsing with intelligent defaults - `common/llama_multiturn_chat.py::chat_with_m` - Multi-turn conversational extraction pattern - `experiments/llama_multiturn_flat_debit_extractor_CBA_` - Full implementation example

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Based on: - OCRBench v2 (10,000 human-verified QA pairs, 38 LMM evaluations) - RD-TableBench (6 VLLMs evaluated: Phi, Llama, GPT-4o-mini, Qwen, GPT-4o, Gemini) - ICDAR-2013 & TabStructDB benchmarks for row/column detection - Empirical testing: Australian bank statement extraction with Llama-3.2-Vision-11B and InternVL3-8B

Date: November 2025