A3 – CUJ Runthrough + Demo

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TL;DR

We researched how SMBs struggle with messy inventory data, then tested OpenRefine and ChatGPT on Smell & Smile's legacy export. OpenRefine handled simple clustering/normalization; complex joins and domain conversions failed. We switched to LLM-assisted transforms via prompt iterations to finish the job. Key insight: the best system mixes automation with user input, ultimately feeding a multi-source, LLM-powered data platform.

User Goal

As a small retailer with a messy legacy inventory system, I want to clean, normalize, and categorize my product data, flagging errors and low stock, so I can reorder with confidence and prepare for an AI-assisted data platform that unifies all my sources.

Persona Description

- Role / Background: Owner-operator of a small fragrance retailer (Smell & Smile);
 responsible for inventory, purchasing, and sales.
- Experience: Comfortable with Excel; first time using OpenRefine or LLMs for data work.
- **Context:** Time-constrained, domain knowledge heavy, limited technical background.

Tools Used

- **OpenRefine** (clustering, faceting, regex transforms)
- Google Sheets (quick checks, buy list filters)
- **ChatGPT** (LLM-assisted regex, column mapping, free-text → structured rules; prompt iteration)
- Excel (initial preview/export)

Summary of Findings

Research & Problem Framing

Before testing tools, the user researched typical SMB inventory issues: duplicate SKUs, inconsistent units (ml/ML/mL/tola), mixed item types (raw materials, finished products, packaging), negative stock, and missing costs. The success metric was: produce a clean, categorized dataset with low-stock flags and explainable steps.

Phase 1 — OpenRefine: quick wins, clear limits

What worked well:

- Clustering: Normalized "Oud 6ml," "OUD 6 ML," and "Oud 6mL" into one label.
- Simple unit fixes: Standardized ml / ML / mL to mL; pcs/PCS → pcs.

Facets: Surfaced anomalies like negative stock and blank costs quickly.

Where it failed:

- Unit conversions: Handling tola → mL was brittle across typos and spacing.
- Compound parsing: Extracting size + unit from messy free-text names often broke.
- Rule collisions: Categorization rules ("tester bottle" vs "bottle of tester oil") became messy chains that were hard to maintain.

Result: OpenRefine handled straightforward normalization, but struggled with domain-specific conversions and edge cases, demanding heavy manual effort.

Phase 2 — Switching to ChatGPT (LLM-assisted transforms)

To go beyond OpenRefine, the user integrated ChatGPT to generate transformations:

- Regex parsing: Extracted size_value and size_unit from strings like "12 ml," ".41 oz," "1 tola."
- Unit conversions: Proposed consistent logic: map tola → 11.66 mL, handle L/cL → mL, leave pcs/kg.
- Categorization rules: Built a keyword table with synonyms/negatives. An _override column was added for human review.

Prompt iteration: Early prompts failed on decimals/hyphens. Adding **dataset-specific examples** improved accuracy. Asking the LLM to generate explanations + test cases produced more reliable patterns.

Outcome: ChatGPT accelerated regex and logic authoring, but results still required checking. Lesson: automation + domain input outperforms either alone.

Phase 3 — Cleaned Data & Actionable Outputs

Combining both tools, the business owner produced a structured, decision-ready dataset:

• Cleaned columns: Standardized names, normalized units (mL, pcs, kg), extracted fields like size_value.

- Custom flags: Added NEG_QTY, MISSING_COST, and REORDER for low stock.
- Categorization: Grouped items into Raw, Packaging, Finished, clarifying what was low or inconsistent.
- Buy list: Exported to Google Sheets, filtering on REORDER produced a supplier-ready restocking list.

Key Insight

SMB data cleaning is socio-technical: tools automate repetitive work, but only business owners can validate messy, domain-specific edge cases. Sustainable workflows must combine automation with lightweight human review.

Recommendations

For Products

- Schema-Aware Import Layer: Auto-detects common SMB schemas and maps columns for review.
- **Domain Rule Packs:** Modular packs. Stored in JSON/YAML for reuse.
- **LLM Transforms w/ Confidence:** Suggestions tagged with confidence. High-confidence (>90%) apply automatically; others flagged for override.
- **Sample-Based Previews:** Let users apply transforms on sample rows and see before/after previews to refine rules.
- Override Columns: Auto-generate _override columns to preserve human judgment.
- **Snapshots & Sandboxing:** Version data cleaning steps like Git commits; easy rollback if errors occur.
- **Provenance & Audit:** Log every transformation (who, when, confidence). Allow replay on new datasets.
- Dashboards: Out-of-the-box connectors for inventory health, buy lists, and error monitoring.

For Future Users

- Start with a small slice of data to test.
- Use OpenRefine for simpler tasks; switch to LLMs for messy parsing.
- Always provide **examples** to LLMs, not vague prompts.
- Keep override columns and save snapshots, mistakes are inevitable.
- Expect context switching; keep notes on steps and timing.

Highlights & Lowlights Table

Task / Moment	Severity	Notes
OpenRefine clustering/unit fixes	Great	Quick normalization; surfaced anomalies fast.
Complex parsing in OpenRefine	Severe	Struggled with edge cases; required custom logic.
LLM regex & rule generation	Great	Faster + more accurate when fed examples.
Categorization & buy list export	Moderate	Needed overrides, but produced actionable output.

CUJ Overview Table

Task	Time	Switches
Open Excel export & inspect messy inventory	5 min	1
Load into OpenRefine, try clustering/facets	15 min	2
Attempt GREL transforms (unit normalization, regex) → docs/tutorials → back to tool	30 min	3
Switch to ChatGPT for regex/unit conversion help; iterate prompts with examples	40 min	3
Test ChatGPT-generated logic back in OpenRefine & Sheets	20 min	2
Move to Google Colab with ChatGPT-generated Pandas pipeline	50 min	2
Debug file import/export & generate clean CSVs	30 min	1
Export flagged data + buy list to Sheets/Data Studio for visualization	25 min	1

Total Time: ~3 hours 35 minutes **Total Context Switches:** 15

Full CUJ Table (Step-by-Step Documentation)

Step	Notes (What + Why)	Screenshot
1	Opened messy Excel export in OpenRefine to inspect inventory. Skipped metadata rows and previewed columns. First goal: see duplicates and blanks.	Fram Date D10/1/2005 7 To Date D10/1/2005 D10/
2	Used clustering and faceting in OpenRefine to merge similar product names. Also normalized simple units.	Company Comp
3 (switch)	Tried to handle complex cases but OpenRefine transforms broke down. Switched to ChatGPT to draft regex + unit conversion logic. Iterated prompts with sample rows.	code,name,quantity,unit,std_quantity,std_unit,cost,supplier,category,Accessories
4	Took the regex and categorization rules generated by ChatGPT, applied them in OpenRefine/Sheets. Created derived columns: size_value, size_unit, standardized_unit. Some mismatches still needed override.	What are put persons of a final fina

5 (switch)	Moved to Google Colab with ChatGPT-generated Pandas script for reproducibility. Cleaned dataset, applied conversion, flagged negatives (NEG_QTY), missing costs, and reorder threshold.	I've uploaded a messy inventory export (Inventory .xlsx) into this Colab notabook. Please help me build a reproducible pipeline in Colab that. 1. Ingests the Excel file (skip the first 6 metadata rows). 2. Normalizes column names (code, name, quantity, unit, cost, supplier). 3. Cleans and standardizes units (e.g., ml., pcs, kg, and convert tola → 11.66 ml.). 4. Flags problems: • Negative or missing quantities • Missing or zero costs • Possible duplicable limite (luzzy matches on name). 5. Categorizes products into exactly three categories • Perfum Oils — amost only limite measured in a liquid unit (mi, tola, L), unless it is clearly Accholicthanal or another solvent. • Emply bottlee — tens wisce names naclude words like "Bottle", "Cap", "Val", "Spray, or Abonuci" • Accessories — everything else (e.g., packaging parts, tools, non-liquid items). 6. Generates three CSV outputs into the Colab environment. • Letter, 2-Leenciv with all defected sissues • BuyList_TYYYY-MB-EO.cs for Perfume Oils below a stock threshold of 20 units, grouped by supplier. Please propose the steps fint, thin generate deterministic Pandas code cells i can run in Colab. Keep Lid use minimal (only for caleporation suspections in readed) at mah and conversions must be inproducible. Also include any Colab specific snippels (e.g., files., upload) for file import, files. download () for recopri)
6	Exported cleaned CSVs to Google Sheets. Used filters to generate a buy list for low-stock oils, grouped by supplier. The final dataset now had standardized names, normalized units, and actionable flags.	Description Comparison Co