Authors: Velasco, J. L<sup>1</sup>; Teixeira, J. T.<sup>1</sup>; Peruchini, M<sup>1</sup>; Modena, G<sup>1</sup>.

#### **Presenters:**

Jefferson Lewis Velasco, MSc - <u>jeffvelasco.crm@gmail.com</u> Júlio Monteiro Teixeira, Dr - <u>juliomontex@gmail.com</u>

UFSC - Federal University of Santa Catarina<sup>1</sup>



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#### Jeff

Jefferson is a PhD candidate in Design at UFSC and a researcher at Lemme Lab. A career civil servant at CIASC since 2010, he currently manages Digital Government projects. His work focuses on data-driven design and data personas to support innovation in public services.

### Areas of Interest:

- Data-Driven Design
- Personas
- Bibliometrics
- Low Resource Contexts





#### Julio Teixeira

Adjunct Professor at UFSC, teaching in the Design Program and in the Graduate Programs in Design (PPGD), and Knowledge Engineering (PPGEGC). Leads the Lemme – Digital Innovation Research Group. Postdoctoral Fellow at the Academy of Art University (San Francisco, USA). PhD in Production Engineering from UFSC, with a research period at the University of Wuppertal (Germany). Master's in Design Management (UFSC) and Bachelor's in Design (UDESC).

### Areas of Interest:

- Generative Als
- CX/UX Journey
- Data-Driven Design











### **Context:**

#### **Problem and Motivation**

- Small organizations face barriers in persona creation:
  - Lack of data science expertise;
  - Complexity of clustering methods;
  - Limited resources for advanced analysis.
- Current methods are designed for experts.
- **Question:** Can AI tools bridge this gap?



### **Context:**

### **Objective**

Evaluate how ChatGPT 4o, through the PersonaCraft methodology, can assist non-experts in creating data-driven personas.

### **Research Question**

How effectively can ChatGPT 40 guide small organizations in executing the core stages of PersonaCraft for persona creation?



### **Dataset Selection**

The dataset used was a publicly available retail customer dataset from Kaggle, containing 3,908 rows of simulated demographic and behavioral data—ideal for testing segmentation methods in small business contexts due to its simplicity and completeness.

Detail Compact	Column			10 of 17 co	lumns '
About this file The CSV file has 17 constatements on DOB	olumns all describing the cu	ustomer's demographics a	nd geographics. Age colu	nn is created using a condit	ional
∞ customer_id = Customer ID	∆ First_Name = First Name	▲ Last_Name = Last Name	∆ gender == Gender	DOB = Date of Birth	<b># AGE</b> Age

https://www.kaggle.com/datasets/harishedison/kpmg-customer-demography-cleaned-dataset



### PersonaCraft Framework

PersonaCraft is a structured framework that guides the creation of data-driven personas through defined stages, combining clustering techniques with descriptive analysis to generate reliable user segments.



PersonaCraft: A novel persona generation methodology that leverages LLMs (Jung et al., 2025)









### **Dataset Overview**

Variable Group	Description	Variables	Headings	
Personal Identification	Used to uniquely identify or describe a person.	customer_id	Customer ID	
Demographics	Attributes related to socioeconomic status, age, and personal traits.	age	Age	
		gender	Gender	
		job_industry_category	Job Industry Category	
		wealth_segment	Wealth Segment	
Purchasing Behavior	Data on purchases or transaction-related behavior.	past_3_years_bike_related_p urchases	Bike Purchases Last 3 Years	
Customer Tenure	Duration of the customer's relationship.	tenure	Customer Tenure	
Assets & Ownership	Indicators of asset ownership	owns_car	Car Ownership	
Location Information	Geographic location of the customer.	state	State	



# Methodology

#### **Data Preparation**

- **Removed irrelevant variables:** (names, adresses, IDs, etc.);
- Classified variables into 5 groups: (Personal Identification, Demographics, Purchasing Behavior, Customer Tenure, Assets & Ownership and Location Information);
- Retained numeric variables in original form for statistical accuracy;
- Prompts adapted to guide GPT through each PersonaCraft stage.



# Methodology

### Clustering

- Clustering Algorithm: k-prototypes (mix of categorical + numeric);
- Cluster Number Decision: Elbow Method  $\rightarrow$  Best at k=5;

#### • Output:

Excel file with cluster labels & PCA visualization of clusters.





# Methodology

### **Statistical Testing**

- Applied Kruskal-Wallis test to check variable significance between clusters.
- Significant variables:
  - Purchase Frequency (p < 0.01);
  - Age (p < 0.01);
  - $\circ$  Customer Tenure (p < 0.01).



# **Prompt Sample**

#### **Initial Prompt**

Hi, I am trying to segment a dataset for data persona creation. I have already analysed variables and determined the best approach is to use k-prototypes. But in order to do that, first I must define the optimal number of clusters for my dataset. Can you help me?

#### Response

Below is a step-by-step guide (with sample code) on how you can determine the optimal number of clusters for **k-prototypes**. The most common approach is an "Elbow Method" based on the **cost** (sometimes called the within-cluster distance) returned by the **k-prototypes** model.

In the k-prototypes algorithm:

- 1. **Numeric attributes** contribute to the distance with the usual Euclidean term.
- 2. **Categorical attributes** contribute to the distance using simple matching (Hamming) distance.

The **cost\_** attribute of a fitted k-prototypes model is a sum of these distances over the entire dataset. By running k-prototypes multiple times with different values of kkk (number of clusters), then plotting or examining how the cost changes, you can look for an "elbow" point to help choose a suitable k.

#### **Example Interaction:**

A non-expert user engages ChatGPT 40 through natural language. The model interprets the request, provides clear guidance, and enables the user to complete the task successfully.

The initial prompt and response are followed by a conversation with detailed instructions that lead to the completion of the task.



# Results

#### Persona Summaries: 5 Personas Identified

- Cluster 1: Older (52), Low purchases, Long tenure;
- Cluster 2: Young (33), High purchases, Short tenure (New, engaged buyers);
- **Cluster 3:** Middle-aged (48), Highest purchase rate, Stable tenure;
- Cluster 4: Very young (31), Low purchases, Short tenure;
- Cluster 5: Older (52), Medium purchases, Longest tenure.



# Results

### **Clusters Descriptions** (using variable frequencies and centrality measurements)

Variable	Values	(1	٢2	(3	<b>C</b> 4	٢5
Gender	Female	468	328	484	295	462
	Male	373	317	471	281	429
	Manufacturing	173	144	185	107	187
	Financial Services	162	131	179	122	172
	n/a	142	102	165	96	150
	Health	122	86	161	83	144
Job Industry	Retail	86	66	85	52	69
Category	Property	46	35	66	46	73
	Entertainment	35	21	30	21	29
	ІТ	29	26	39	27	29
	Agriculture	25	25	29	10	24
	Telecommunications	21	9	16	12	14
Wealth Segment	Mass Customer	401	328	498	275	449
	High Net Worth	229	162	227	157	220
	Affluent Customer	211	155	230	144	222

Variable	Values	(1	С2	٢3	C4	(5
Car Ownership	Yes	432	338	472	280	4 <mark>4</mark> 9
	No	409	307	483	296	442
State	New South Wales	456	330	530	316	457
	Victoria	214	155	229	147	253
	Queensland	171	160	196	113	181
Age	Mean	52,11	32,95	47,86	31,25	52,55
	Median	51	32	47	30	51
	Mode	45	27	44	28	44
Bike Purchases Last 3 Years	Mean	14,06	65,38	85,90	23,45	47,22
	Median	14	66	87	25	47
	Mode	2	68	98	27	53
Customer Tenure	Mean	12,34	7,45	11,41	6,82	13,05
	Median	12	6	12	5	13
	Mode	11	1	12	2	18



# Results

### Key Insights

- Numeric variables are critical especially purchase frequency and age;
- Demographic labels (like gender or job industry) don't differentiate clusters;
- GPT successfully executed technical steps via prompting without coding;
- The process significantly lowers the barrier for persona creation in small organizations.



# **Conclusion & Future Work**

#### Conclusion

- ChatGPT 4o can guide non-experts through persona creation tasks;
- Effective for small organizations lacking analytics teams.

#### **Future Work**

- Test with real, richer datasets;
- Combine LLM output with stakeholder validation;
- Explore automation of prescriptive tasks (e.g., customer journey design),

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# Thank you!

# **Empowering Persona Creation in Small Organizations** Evaluating ChatGPT 40 for Clustering and Analysis using PersonaCraft

#### **Presenters:**

Jefferson Lewis Velasco, MSc - <u>jeffvelasco.crm@gmail.com</u> Júlio Monteiro Teixeira, Dr - <u>juliomontex@gmail.com</u>

UFSC - Federal University of Santa Catarina<sup>1</sup>

