**🔎 How HCES Data Fits Into Your Model**

**Your Formula:**

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HCES data gives you **the "Income" and "Cultural Fit" part of this formula**, but indirectly (through consumption patterns).

**1. Table 3.2.1 → Average MPCE (Monthly Per Capita Consumption Expenditure)**

* **What it is:** Average money spent per person per month (proxy for income, since spending tracks earnings).
* **Why useful:** Instead of assuming everyone earns ₹35,000, you can **use state/district-level averages**.  
  Example:
  + Kerala Urban MPCE ≈ ₹4,000
  + Bihar Rural MPCE ≈ ₹1,200  
    → A café in Kerala has a much larger potential spend base than in rural Bihar.

📌 **How it plugs in:**  
Income = MPCE × Population in your 5km radius → gives you **local spending power**.

**2. Table 3.2.2 → Trend in Consumption (Nominal & Real Prices)**

* **What it is:** Shows growth in consumption over time (inflation-adjusted).
* **Why useful:** Lets you forecast how **spending will change in future years**.
  + If real MPCE is growing at 5% annually in your region, you can project higher revenues.

📌 **How it plugs in:**  
Adjusts your **Market\_Factors** denominator to account for inflation and growth.

**3. Table 3.2.5 → Food vs Non-Food Expenditure**

* **What it is:** Breakdown of how people spend (e.g., 55% on food, 45% on non-food like health, education, recreation).
* **Why useful:**
  + If a region spends **more on eating out/food services**, it’s good for restaurants/cafés.
  + If a region spends **more on healthcare**, gyms/clinics will do better.

📌 **How it plugs in:**  
This helps refine **Business\_Type multiplier** (café, gym, salon, etc.).

**4. Table 3.2.6–3.2.7 → Cereal vs Non-Cereal Consumption**

* **What it is:** Shows diet preferences.
* **Why useful:**
  + High cereal/tea regions → tea shops do better.
  + Low cereal/high milk/coffee spend → cafés do better.

📌 **How it plugs in:**  
Helps calculate **Cultural\_Fit** score (0.8 for coffee in tea regions, 1.2 in coffee-preferring regions).

**5. Table 3.2.12 → MPCE Across Social Groups**

* **What it is:** Breaks spending by caste/community/religion/other social groups.
* **Why useful:** Some groups spend more on food outside home, some less.  
  Example: Urban middle-class households may spend more on cafés.

📌 **How it plugs in:**  
Fine-tunes **Income & Cultural\_Fit multipliers**.

**6. Table 3.2.14 → Inequality in Distribution of MPCE**

* **What it is:** Gini coefficient & distribution of spending.
* **Why useful:**
  + High inequality means only a small % can afford your business → lowers **confidence score**.
  + Low inequality means more stable demand.

📌 **How it plugs in:**  
Used in **Confidence Level** output of your model.

**7. Summary Statements (S1–S68)**

* **What they are:** Detailed tables (state × rural/urban × household size × expenditure groups).
* **Why useful:**
  + Lets you get **granular local data** (instead of just averages).
  + Example: Urban, 3-member households in Maharashtra spend ₹X on food → more precise café model.

📌 **How it plugs in:**  
You merge this with **Census population** and **Google Maps traffic/competition data** → full localized prediction.

**🛠 How It All Connects (Example)**

Let’s say you want to open a café in **Lucknow**:

1. **Population (Census):** 5,000 people in 5 km radius.
2. **Income (HCES MPCE):** Avg MPCE in UP Urban = ₹2,500.  
   → Spending power ≈ ₹12.5M/month in that 5km radius.
3. **Food vs Non-Food (HCES):** 55% food → ₹6.8M food market.
4. **Cultural Fit (HCES cereals/tea vs coffee):** High tea region → café score 0.8.
5. **Competition (Google Maps):** 3 cafés nearby → adjust down.
6. **Traffic Density (OSM/Google):** 7.5/10 → adjust up.
7. **Seasonal Factor (Festivals Q4):** +25% boost.

👉 Your model outputs:  
**Monthly Revenue ~ ₹45,000, Yearly ₹5.4L, Confidence 82%.**