**📘 Documentation: Customer Credit Risk & Financial Overview Dashboard**

**📌 Project Overview**

This Power BI dashboard presents a comprehensive analysis of customer credit risk and financial profiles based on various demographic and financial parameters. The aim is to assist financial institutions and analysts in understanding customer behavior, identifying risk patterns, and supporting informed decision-making in credit and loan management.

**📊 Key Metrics**

| **Metric** | **Value** |
| --- | --- |
| Total Customers | 149.98K |
| Average Monthly Income | 6.67K |
| Average Debt Ratio | 0.35K |
| Avg. Open Credit Lines | 0.01K |

**📈 Visual Analysis & Insights**

**1. Monthly Income by Education and Gender**

* **Post-Graduate** customers (particularly **males**) have the **highest total income**.
* A consistent income disparity exists between genders across all education levels.

**2. Number of Dependents and Debt Ratio by Age**

* Debt ratio varies across age groups with visible spikes in specific ranges.
* **Dependents count** is **highest among middle-aged individuals**.

**3. Education by Region**

* Distribution:
  + **East**: 43.95K
  + **Central**: 34.09K
  + **North**: 27.9K
  + **West**: 23.49K
  + **South**: 20.55K
* **East and Central** regions show the highest educational representation.

**4. Monthly Income by Region and Occupation**

* **Non-officers** in the **Central** region lead with a total of **131.06M**.
* **Self-employed** customers in the **North and West** also contribute significantly.

**5. Number of Dependents by Housing Type**

* **Rented Homes**: 63K dependents
* **Owned Homes**: 48K dependents
* Dependents are more common in rented households.

**6. Dependents by Occupation & Credit Risk (Good/Bad)**

* **Non-officers** dominate both **Good** and **Bad** credit risk categories.
* Dependents are more frequent among the **Good credit** group.

**7. Monthly Income by Credit Risk and Housing**

* **Good credit - Owned House**: +0.94bn
* **Bad credit - Rented House**: -0.50bn
* Clear financial stability difference across credit and housing types.

**🛠️ Tools & Technologies Used**

* **Power BI Desktop**
* **DAX (Data Analysis Expressions)**
* **Slicers, Filters, and Bar/Column Charts**
* **Custom Formatting & Layout**

**📁 File Contents**

├── Task\_1\_2.pdf # Dashboard report overview (visual export)

├── Dashboard.pbix # Power BI dashboard file (not uploaded here)

├── README.md # GitHub overview and documentation

├── Documentation.md # This file

**📌 Use Cases**

* **Credit Risk Profiling** – Identify customers with higher risk profiles.
* **Demographic Targeting** – Understand financial behavior across age, gender, education, and housing.
* **Strategic Financial Planning** – Optimize regional strategies based on income and education data.
* **Operational Decision Making** – Use data-driven visuals to support loan approval or intervention strategies.

**🔗 Related Links**

* 🧵 **LinkedIn Post**: [View the Day 2 LinkedIn Post](https://www.linkedin.com/posts/putuka-ramanjaneyulu-2128r_power-bi-activity-7331201224106549248-3A_s?utm_source=share&utm_medium=member_desktop&rcm=ACoAAD2ia5EB1oVSVZZwKYH5dxER-gZNWMmZj-k) *(update after publishing)*
* 💻 **GitHub Repository**: [Project Repository](https://github.com/PutukaRamanjaneyulu/Credit_Card_Analysis) *(update with actual repo)*

**📬 Contact**

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