

Configuration Manual

MSc Research Project Msc in Fintech (MSCFTD1)

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MSc Project Submission Sheet

School of Computing

Student Name:	Fengly Anggrian					
Student ID:	X22183442					
Programme:	MSc in FinTech (MSCFTD1)		20	2023/2024		
Programme:	Research Project					
Module:	Brian Byrne					
Submission	12 August 2024					
Due Date: Project Title:	Exploring Conventional Banks and E-commerce Synergies in Jakarta, Indonesian Financial Landscape					
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Word Count:		Page Co	·unt:			
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Signature:	Tenter					
	12 August 2024					
Date:						
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Configuration Manual

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1 Section 1

This section will describe the analysis process carried out in the topic "Exploring Conventional Banks and E-commerce Synergies in Jakarta, Indonesian Financial Landscape" and how to implement it sequentially. Step by step will be described clearly as real evidence of the use of the system in this project.

2 System Configuration

2.1 Software Specification:

Tools used in this project:

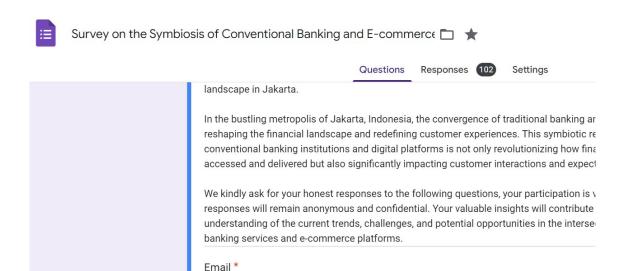
- Google form distributed to all respondents and the results processed in excel form to become a dataset.
- The dataset is then tidied up before being uploaded to Google Colab for further analysis.
- In Google Colab, all processes from data description, factor analysis to predictive modeling are executed.

2.2 Hardware Specification:

- MSI Titan 18, 512 GB SSD, 16GB RAM
- Processor: AMD Ryzen 3 4000H with Radeon Graphics

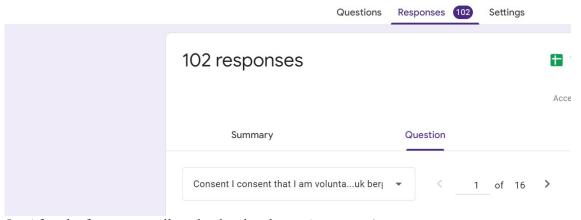
3 Data Generation Steps

- 1. Open Gform in Google Chrome
- 2. Choose 'Blank Form'
- 3. Create a survey

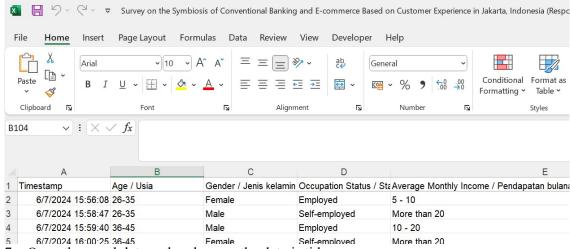


4. Start to make all the questions that you need.





- 5. After the form sent, collect the data by choose 'responses'.
- 6. You can view the data in excel format by choose 'View in Sheets', then you can download it.



7. Open the excel data and make sure the data is tidy.

```
Final Code of Thesis - various latent factor.ipynb 
              File Edit View Insert Runtime Tools Help All changes saved
            + Code + Text
  Q \bigvee_{im} [1] !pip install factor_analyzer semopy
 {x}
                     # Importing necessary libraries
                      import numpy as np
 ⊙
                      from sklearn.preprocessing import LabelEncoder
                       from google.colab import files
 # Upload the data file
8. Open Google Colab in Google Chrome and choose new notebook, then rename with
         the topic and author name.
                  [2] # Strip any leading/trailing whitespace from the col
                                      df.columns = df.columns.str.strip()
9. Display Column name to make sure there is no mistake.
 [3] import pandas as pd
                import numpy as np
                import matplotlib.pyplot as plt
               import seaborn as sns
                from sklearn.preprocessing import LabelEncoder
               from \ factor\_analyzer \ import \ FactorAnalyzer
               from semopy import Model, Optimizer
               # Drop the timestamp column if it exists
               df = df.drop(columns=['Timestamp'], errors='ignore')
               # Rename the columns to Q1, Q2, ..., Q15
               question_mapping =
                       "Age / Usia": "Q1",
                       "Gender / Jenis kelamin": "Q2",
                       "Occupation Status / Status Pekerjaan": "Q3",
"Average Monthly Income / Pendapatan bulanan rata-rata": "Q4",
                       "How Frequently do you use traditional banking services?": "Q5",
                       "How frequently do you engage in e-commerce activities?": "Q6",
                       "How would you rate the convenience of traditional banking services in Indonesia? (Scale: 1-5, 1 being not convenient, 5 being not convenient, 6 being
10. Label the question with simple label.
    [4] # Display the column names
                  print("Column names:", df.columns.tolist())
       To Column names: ['Q1', 'Q2', 'Q3', 'Q4', 'Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10', 'Q11', 'Q12', 'Q13',
              from semopy import Model
                  from factor_analyzer import FactorAnalyzer
                  from semopy import calc_stats
                  model_desc = '''
                  F1 =~ Q5 + Q7
                  F2 =~ Q8 + Q11 + Q12
                  F3 =~ Q6 + Q9 + Q10 + Q13
                  F4 =~ Q14 + Q15
```

11. Propose the model for testing

Make Model

```
[7] # Calculate and print fit model statistic
        stats = calc_stats(model)
        print(stats)
        # Get CFI
        cfi = stats['CFI']
        print(f'Comparative Fit Index (CFI): {cfi}')
              DoF DoF Baseline
                                      chi2 chi2 p-value chi2 Baseline
        Value
               38
                             55 40.288529
                                               0.369336
                                                            786.527733
                   GFI
                            AGFI
                                       NFI
                                                TLI
                                                        RMSEA
                                                                     AIC
        Value 0.948777 0.925861 0.948777 0.995472 0.024419 55.210029
                     BIC
                            LogLik
        Value 128.709268 0.394986
        Comparative Fit Index (CFI): Value
                                            0.996872
        Name: CFI, dtype: float64
   [8] import pandas as pd
        import numpy as np
        def cronbach_alpha(df):
12. Execute CFA
   [9] import pandas as pd
        from factor analyzer import calculate kmo, calculate bartlett
        # Assuming df is your DataFrame and the columns Q5 to Q15 are
        question_columns = ['Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10', 'Q11
        # Select only the columns for the questions
        df_questions = df[question_columns]
        # Calculate KMO
        kmo_all, kmo_model = calculate_kmo(df_questions)
        print(f'KMO: {kmo model}')
13. Execute EFA
```

```
os [15] import pandas as pd
        import numpy as np
        from sklearn.decomposition import PCA
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import StandardScaler
        # Choose relevant columns for analysis
        columns_of_interest = ['Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10', 'Q11', 'Q12']
        df = df[columns_of_interest]
        # Make sure there is no mssing values
        df = df.dropna()
        # Data standardization
        scaler = StandardScaler()
        df_scaled = scaler.fit_transform(df)
        # Do PCA
        pca = PCA()
        pca.fit(df scaled)
        # Get eigenvalues
```

14. Conduct PCA and get eigenvalue.

```
v [16] # Getting the load factor
        loadings = pca.components_.T * np.sqrt(pca.explained_variance_)
        # Create a DataFrame to ease interpretation
        loadings_df = pd.DataFrame(loadings, columns=[f'PC{i+1}' for i in range(len(eigen
  import pandas as pd
        import numpy as np
        from sklearn.preprocessing import StandardScaler
       from sklearn.decomposition import FactorAnalysis
        # Data standardization
        scaler = StandardScaler()
       data_scaled = scaler.fit_transform(df)
       # Conducting Factor Analysis
       fa = FactorAnalysis(n_components=3)
       factors = fa.fit_transform(data_scaled)
       # Obtaining factor loadings
       loadings = fa.components_.T
        # Calculate SS Loadings
         - loadings - nn sum(nn squano(loadings) avis-0)
```

15. Get SS Loading Score

```
# Create factor scores based on the provided questions

df['Conventional_Banking_Service_Quality'] = df[['Q5', '

df['Security_of_Banking_System'] = df[['Q8', 'Q11', 'Q12'

df['Ecommerce_Effect'] = df[['Q6', 'Q9', 'Q10', 'Q13']].

df['Readiness_to_Adopt'] = df[['Q14', 'Q15']].mean(axis=

# Create customer experience score

df['customer_experience'] = df[['Q9', 'Q10', 'Q14', 'Q15']]
```

16. Make Model for Regression and Random Forest

```
v [25] !apt-get install graphviz -y
        !pip install diagrams
        !pip install python-graphviz
        from diagrams import Diagram, Cluster, Edge
        from diagrams.onprem.client import User
        graph_attr = {
            'splines': 'spline', # Keep using splines for curved lines
            'nodesep': '0.3', # Horizontal distance between nodes
            'ranksep': '0.5'
                                # Vertical distance between node ranks/rows
        with Diagram("TAM Model with Relevant Factors", show=False, filename="tam_diagram_revised", direction='LR
            # External Factors
            conventional_banking_quality = User("Conv. Bank\nQuality")
            security_of_banking_system = User("Security")
            ecommerce_effect = User("E-commerce\nEase")
            readiness to adopt = User("Readiness")
            # TAM Constructs
            perceived_usefulness = User("Usefulness")
```

17. Visualise Tam Model

18. With Google Colab, it is possible to run a lot of analysis to get more comprehensive result, so that the result can be used to make conclusion such as the result below.

→ Regression Model

Mean Squared Error: 0.029558252962477747

R-squared: 0.9594865903451354

Feature: Conventional_Banking_Service_Quality, Impo Feature: Security of Banking System, Importance: 0.

Feature: Ecommerce_Effect, Importance: 0.3193 Feature: Readiness_to_Adopt, Importance: 0.4867

Random Forest Classifier

Accuracy: 0.6190476190476191

Classification Report:

	precision	recall	f1-score	suppo
1	1.00	1.00	1.00	
4	0.00	0.00	0.00	
5	0.59	0.91	0.71	
			0.00	