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## ANALYTICS REPORT

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**TO:** TAIWANESE CREDIT CARD COMPANY MANAGEMENT  
**FROM:** DANIEL MONHEIT  
**SUBJECT:** ANALYSIS OF CREDIT CARD DETERMINATION AND DEFAULT RISK  
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### *Introduction*

This report was created to analyze the factors that influence credit limits and the likelihood of default using a dataset of 24,286 observations. The goal was to determine whether demographic variables, such as gender, age, education, and marital status, impact credit limits, and to evaluate what factors influence default risk. Multiple regression analysis was used to model both credit limit and probability of default. The results show that credit limits are significantly influenced by age, education, and marital status, while default risk is primarily driven by payment behavior, though the default model has limited explanatory power. The analysis does not indicate gender bias against women in credit limit assignment, but additional variables such as income, credit score, and payment history are recommended to improve both models. This report will first present the credit limit model, followed by the default model, and conclude with recommendations for improving the analysis.

### *Data Analysis*

This section presents the results of the regression analyses used to examine the factors influencing credit limits and the probability of default. The models evaluate how demographic and financial variables impact each outcome and assess their statistical significance and predictive power. Predictions are also generated for hypothetical individuals to demonstrate how the models can be applied in practice.

#### Credit Limit Model

$$\widehat{\text{Credit Limit}} = 375.52 + 363.47(\text{Female}) - 1141.99(\text{High School}) \\ + 2319.91(\text{Grad School}) + 2977.63(\text{Married}) + 118.16(\text{Age}) \\ - 67.03(\text{Married} * \text{Age})$$

The  $R^2$  of 0.1187 indicates that 11.87% of the variation in credit limits is explained by the model. The standard error of 4029.41 suggests predictions are off by about \$4,029 on average. Holding all else constant, credit limits are higher for females (+\$363.47) and those with graduate degrees (+\$2,319.91), but lower for individuals with only a high school education (–\$1,141.99). Age increases credit limits (+\$118.16 per year), though this effect is smaller for married individuals due to the negative interaction term (–\$67.03). Overall, marriage increases credit limits at younger ages, but the effect declines as age increases.

Here I will predict the credit limit of a 40-year-old, single, male with a university degree:

$$\widehat{\text{Credit Limit}} = 375.52 + 118.16(40) = 5101.92$$

The predicted credit limit for a 40-year-old, single, male with a university degree is \$5,101.92

### Chance of Defaulting Model

$$\widehat{Default} = 0.22701 + 0.000006653(Avg. Bill) - 0.000167688(Avg. Payment) + 0.000883388(Age) - 0.029864635(Female)$$

The  $R^2$  of 0.0152 indicates that 1.52% of the variation in the chance of defaulting is explained by this model. The standard error of 0.4118 suggests that, on average, the predicted default probabilities differ from actual outcomes by about 0.412. Holding all else constant, higher average bill amounts are associated with a slightly higher probability of default (+0.000006653 per unit of Avg. Bill), whereas higher average payment amounts are associated with a lower probability of default (−0.000167688 per unit of Avg. Payment). Age slightly increases the chance of default (+0.000883388 per year), while females have a lower probability of default than males (−0.0299). Overall, average payment behavior has the strongest impact on default risk in this model, with larger payments substantially reducing the likelihood of default.

Here I will predict the chance of defaulting for someone who is 30 years old, female, has an average bill amount of \$800, and average payments of \$700:

$$\widehat{Default} = 0.22701 + 0.000006653(800) - 0.000167688(700) + 0.000883388(30) - 0.029864635(1) \approx 0.1116$$

So, the predicted chance of defaulting for a 30-year-old female with an average bill of 800 and average payments of 700 is about 0.112, or 11.2%.

### Recommendation

The results do not suggest that the method for assigning credit limits is biased against women. In the credit limit model, the coefficient on the female variable is positive and statistically significant, indicating that females receive higher credit limits than males, holding all else constant. This contrasts with the earlier finding that men have higher average bill amounts, which suggests that men may spend more despite having lower credit limits, likely due to differences in spending behavior or other financial characteristics not included in the model. However, before drawing strong conclusions about gender bias, important variables such as income, credit score, credit utilization, employment status, debt-to-income ratio, and payment history should be included to better isolate the true effect of gender.

The model for predicting the chance of defaulting is not very accurate, as indicated by the very low R-squared of 0.015, meaning it explains little of the variation in default behavior. While some variables are statistically significant, the model omits key drivers of default risk. To improve its accuracy, variables such as credit limit, credit utilization rate, detailed payment history (e.g., missed or late payments), income, employment stability, and total outstanding debt should be included, as these are more directly related to an individual's likelihood of defaulting.

### Conclusion

The analysis shows that credit limits are significantly influenced by age, education, and marital status, while the probability of default is primarily driven by payment behavior, though the default model has limited explanatory power. There is no evidence of gender bias against women in credit limit assignment, as females are associated with higher limits, despite men having higher average bill amounts. To better understand these relationships, future analysis should include variables such as income, credit score, credit utilization, and payment history. Next steps include refining both models by incorporating these additional variables to improve predictive accuracy and better capture real-world financial behavior. Based on these findings, it is recommended that further data be collected and analyzed before making any conclusions about credit policy or risk assessment practices. Please feel free to contact me with any questions or for further analysis at [demonheit@arizona.edu](mailto:demonheit@arizona.edu).

### Technical Appendix

Figure 1 – Credit Limit Model

| Regression Statistics |                     |                       |               |                |                       |                  |
|-----------------------|---------------------|-----------------------|---------------|----------------|-----------------------|------------------|
| Multiple R            | 0.34446841          |                       |               |                |                       |                  |
| R Square              | 0.118658485         |                       |               |                |                       |                  |
| Adjusted R Square     | 0.118440682         |                       |               |                |                       |                  |
| Standard Error        | 4029.410306         |                       |               |                |                       |                  |
| Observations          | 24286               |                       |               |                |                       |                  |
| ANOVA                 |                     |                       |               |                |                       |                  |
|                       | <i>df</i>           | <i>SS</i>             | <i>MS</i>     | <i>F</i>       | <i>Significance F</i> |                  |
| Regression            | 6                   | 53072354286           | 8845392381    | 544.7962596    | 0                     |                  |
| Residual              | 24279               | 3.94197E+11           | 16236147.41   |                |                       |                  |
| Total                 | 24285               | 4.4727E+11            |               |                |                       |                  |
|                       | <i>Coefficients</i> | <i>Standard Error</i> | <i>t Stat</i> | <i>P-value</i> | <i>Lower 95%</i>      | <i>Upper 95%</i> |
| Intercept             | 375.5185739         | 159.8110637           | 2.349765813   | 0.018793189    | 62.27902914           | 688.7581187      |
| Female (d)            | 363.4674021         | 53.40246008           | 6.806192103   | 1.02549E-11    | 258.7952855           | 468.1395187      |
| High School (d)       | -1141.991732        | 75.14980966           | -15.19620259  | 6.49726E-52    | -1289.289996          | -994.6934687     |
| Grad School (d)       | 2319.908965         | 57.91258105           | 40.05880799   | 0              | 2206.396733           | 2433.421197      |
| Married (d)           | 2977.625328         | 235.0226114           | 12.66952703   | 1.13986E-36    | 2516.966509           | 3438.284146      |
| Married (d) * Age     | -67.02773391        | 6.399293277           | -10.47424005  | 1.28654E-25    | -79.57074356          | -54.48472426     |
| AGE                   | 118.1635478         | 4.71984469            | 25.03547374   | 1.358E-136     | 108.912361            | 127.4147346      |
| Daniel Monheit        |                     |                       |               |                |                       |                  |

*Figure 2 – Chance of Defaulting Model*

| Regression Statistics |              |                |              |             |                |              |
|-----------------------|--------------|----------------|--------------|-------------|----------------|--------------|
| Multiple R            | 0.123110274  |                |              |             |                |              |
| R Square              | 0.01515614   |                |              |             |                |              |
| Adjusted R Square     | 0.014993899  |                |              |             |                |              |
| Standard Error        | 0.411773422  |                |              |             |                |              |
| Observations          | 24286        |                |              |             |                |              |
| ANOVA                 |              |                |              |             |                |              |
|                       | df           | SS             | MS           | F           | Significance F |              |
| Regression            | 4            | 63.35843009    | 15.83960752  | 93.41740387 | 5.5447E-79     |              |
| Residual              | 24281        | 4117.022036    | 0.169557351  |             |                |              |
| Total                 | 24285        | 4180.380466    |              |             |                |              |
|                       | Coefficients | Standard Error | t Stat       | P-value     | Lower 95%      | Upper 95%    |
| Intercept             | 0.227005837  | 0.011482549    | 19.76963858  | 2.59766E-86 | 0.204499333    | 0.24951234   |
| Avg. Bill             | 6.65287E-06  | 1.34403E-06    | 4.949940451  | 7.47333E-07 | 4.01849E-06    | 9.28725E-06  |
| Avg. Payment          | -0.000167688 | 9.23207E-06    | -18.16368615 | 3.05913E-73 | -0.000185784   | -0.000149593 |
| AGE                   | 0.000883388  | 0.000290516    | 3.040756177  | 0.002362363 | 0.000313959    | 0.001452818  |
| Female (d)            | -0.029864635 | 0.00543686     | -5.492993088 | 3.99141E-08 | -0.040521216   | -0.019208054 |
| Daniel Monheit        |              |                |              |             |                |              |

### *Original Introduction/Conclusion – Pre-AI*

#### *Original Introduction*

This report looks at what factors affect credit limits and the chance of default using a dataset of 24,286 observations. The goal was to see how variables like age, gender, education, and marital status impact credit limits, and what factors influence whether someone defaults. Multiple regression analysis was used to build both models. The results show that credit limits are mainly affected by age, education, and marital status, while default risk is mostly influenced by payment behavior, although that model is not very strong. The analysis does not show bias against women in credit limits, but adding variables like income, credit score, and payment history would likely improve the models. This report will first explain the credit limit model, then the default model, and finish with recommendations.

#### *Original Conclusion*

The analysis shows that credit limits are affected by factors like age, education, and marital status, while the chance of default is mostly influenced by how much people pay compared to what they owe. The model does not show bias against women, since females are associated with higher credit limits, even though men tend to have higher average bills. To better understand these results, it would be helpful to include more variables like income, credit score, and payment history. The next step would be to improve the models by adding these factors to make them more accurate. Based on this, more data should be analyzed before making any major decisions about credit policies, and I can be contacted with any questions or for further analysis.

*Sources Consulted*

OpenAI. (2026). ChatGPT (Apr 16 version) [Large language model].  
<https://chat.openai.com/chat>