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A Study of Impact of Income on Consumer Attitude, Motivation, and Awareness towards Credit Scores Among Women Professionals

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ABSTRACT

This study investigates the relationship between an individual's level and their attitude, motivation, and awareness concerning CIBIL scores. Utilizing a quantitative approach with data from 150 participants, the research employed descriptive statistics, correlation analysis, and multiple linear regression. The findings consistently demonstrate that income level does not significantly predict consumers' attitudes, motivations, or awareness regarding credit scores. Despite intuitive assumptions, the analyses revealed very low explanatory power of income for these variables, with all regression models and individual income coefficients being statistically non-significant. This suggests that actors beyond income may be more influential in shaping financial perceptions and knowledge related to credit scores, highlighting implications for broad-based financial literacy initiatives.

***Keywords**: Cibil Score, Awareness, Women Professionals, Attitude, Motivation.*

Introduction

In today's interconnected global economy access to credit has become an essential element of financial engagement and personal economic stability. from security investments like home loan and educational financing to managing everyday expenditures through credit cards and individuals capacity to obtain and responsibility utilise credit profoundly shapes their quality of life and opportunities for economic advancement full stop this whole particular significance in rapidly evolving economy such as India, where formal credit market are undergoing substantial expressing a robust credit reporting infrastructure that benefits both financial institutions and their clients.

Central to India's credit landscape is the credit information Bureau (India) Limited (CIBIL)l, recognised as the Nation's pioneering and leading credit information agency. Established to serve as a centralised responsibility for credit data, CIBIL systematically gathers and maintains comprehensive records of individual payment histories pertaining to various loan and credit cards. These vital records, submitted on a monthly basis by member banks and other financial entities are subsequently compiled into a credit information report (CIR) and a numerical CIBIL Score, which typically ranges from 300 to 900. This score functions as a critical indicator of an individual's creditworthiness, empowering lenders to make well informed decisions concerning loan approvals, applicable interest rate and credit limits for consumers. A favourable CIBIL score translates into expedited loan processing, more advantageous terms and broader financial prospects.

While the operational mechanism and inherited value of CIBIL are widely acknowledged, a comprehensive understanding of the diverse factors that influence individuals' interaction with and perception of their credit remains an active area of research. Specifically this investigation focuses on exploring the connection between an individual income level and their attitude, motivation and awareness pertaining to CIBIL scores in this context, attitude refers to an individual prevailing disposition and convictions regarding credit and financial management; motivation encompasses the internal and external impulses that drive financial action and awareness denotes the cognitive understanding and recognition of CIBIL existence and its fundamental function.

Conventional perspectives often posit direct correlation between higher income and enhance financial literacy, self-assurance and proactive engagement with financial instruments. Nevertheless, the intricacies of financial behaviour are multifaceted, and the precise influence of income on psychological constructs such as attitude and Motivation particularly concerning a specialised concept like a Credit score warrant rigorous empirical examination gaining inside into these relationships is paramount for developing effective financial literacy programs and credit counselling services. Should income prove to be an insignificant predictor of these variables it would suggest that intervention strategies should be broadly inclusive rather than narrowly targeting specific income segments. Conversely if a strong correlation is identified, it could inform the development of most precise and effective initiatives.

Consequently, this research endeavours to systematically analyse the degree to which an individual's income level impacts their disposition towards credit score, their drive to manage them effectively, and their overall understanding of CIBIL's operations and implications. Through a meticulous analysis of these independencies this study aims to contribute valuable insights to the existing academic discourse on financial behaviour, credit literacy and consumer psychology within the unique Indian contexts ultimately guiding efforts to cultivate greater financial confidence and responsible credit management practices among the population.

Literature Review

The evolving financial landscape has increasingly highlighted the importance of credit risk management for financial institutions. A number of studies have explored various aspects of credit scoring, its significance and the factors that influence it. This review synthesizes key findings from several notable papers, providing a comprehensive overview of the research on this topic.

The foundational importance of credit risk management is emphasized by Batista (2019), who notes that the increase in bad debts has compelled financial institutions to enhance their credit risk controls. The primary goal of this control is to reduce default risk, which rises with more permissive credit policies, leading to significant losses from uncollectible loans. The Basel ll agreement was a major step in addressing this by recommending tighter credit risk controls, with credit scoring emerging as a key practice to predict debtor behaviour. Building on this, **Ahmed and Rajaleximi (2019)** highlight the growing relevance of credit risk in the modern era, where technological advancements have led to more frequent financial transactions and, consequently a higher risk of fraud and financial crises. They stress that financial institutions now consider it insecure to approve loans without proper due diligence, such as Know Your Customer (KYC) protocols. Their empirical study focusses on credit scoring as a strategy for credit risk management, which helps to clearly estimate the creditworthiness and trustworthiness of customers based on their payment and credit histories.

The impact of external economic events on credit scores has also been a subject of research. **Somani et al. (2021)** examined how the COVID- 19 pandemic affected customers' financial situations and subsequently, their CIBIL scores. Despite government and central bank interventions, many individuals struggled to maintain their scores due to factors like loans moratoriums and restructuring. The study underscores the significance of the CIBIL score in loan application acceptance and interest rates, particularly in the context of economic downturns.

Laxmanan and Sankaramuthukumar(2017) provide a historical and contemporary perspective on credit scoring. They note the while the concept was once narrowly associated with large purchases, it is now a sophisticated tool that can affect rates for various goods and services, including insurance and cell phones plans. The authors point out a significance lack of awareness among many Indians about the credit scoring system and its importance until they are phased with a major purchase. Their research specifically attempts to investigates the relationship between a respondent's monthly income and their financial understanding.

Further elaborating on the mechanics and purpose of credit scoring, **Sajan (2021)** describes it as a system that allows lenders to assess ton assess a borrower's creditworthiness and repayment capacity. The need for a credit bureau in india arose from a financial crisis, and institutions like CIBIL have since transformed how loans are provided and managed. The articles primary focus is to gauge the level of awareness about credit scoring among commercial banks customers in the kerala region.

The practical application of credit scoring methods is detailed by **Selvarasu et al. (2015)**, who explain the different type of loan products offered by commercial banks and the various scoring methods used to classify risk. They outline both traditional and advanced statistical methods for evaluating credit emphasizing that credit evaluation is a crucial step in a bank's decision- making process the quality of a bank's loan portfolio is a primary determinant of its profitability and survival, making credit scoring as indispensable tool for mitigating bad credit risk.

From a technological standpoint, **Rani et al. (2020) and Lohokare et al. (2017)** Propose Innovative methods to enhance the CIBIL system. Rani et al. describe an improved, user friendly system where citizens can check their CIBIL score and eligibility for loans, while all addressing issues like being blacklisted. Lohokare et al. suggest a novel approach using smartphone application to gather data from SMS notifications about transactions and social media to determine a person's social standing this data could then be used in conjunction with artificial neural networks to calculate a final credibility score, offering an alternative method for individuals with no prior credit history.

Finally, **Daisy P.K(2016) and Niharika et al. (2017)** provide a clear overview of CIBIL's functions. Daisy's research focuses on how CIBIL collects data on an individual's payment history to generate credit reports, which are then used by banks to make decisions on loans and credit cards. Niharika et al. echo this by describing CIBIL as India's first credit information company, which creates value for financial institution by providing objective data to manage risk. They also identify a significant problem. CIBIL cannot calculate a credit score for new users without a credit history, a gap their paper seeks to address with a proposed solution.

In summary, the literature highlights that credit scoring is a critical tool for risk management in the financial sector. Studies have explored its role in loan approval, the impact of economic events, and the varying levels of consumer awareness. While some research has touched upon the relationship between income and financial understanding, the literature shows a continuous evolution of methods and a persistent focus on improving credit risk evaluation in an increasing complex financial environment.

Research Methodology

This study employed a quantitative research design to investigate the relationship between income and consumer's attitude, motivation, and awareness concerning CIBIL scores. The methodology was structured to ensure a systematic and rigorous analysis of the data, providing of foundation for drawing statistically valid conclusions.

Research Design and Data Collection

A descriptive and analytical research design was adopted. A survey was conducted using a structured questionnaire, which was developed together primary data from participants. The questionnaire included a mix of demographic questions and a series of statements designed to measure the key variables of attitude, motivation, and awareness. These statements were crafted using a Likert scale format to capture the nuanced perceptions of the respondents.

Sampling and Sample Size

The study utilized a convenience sampling method to select participants. This non-probability sampling technique was chosen to facilitate the collection of data from a readily available group of a individuals. The sample size for this research was 150 **participants**, which is considered adequate for statistical analysis and for detecting significant relationships within the data.

Variable Measurement

The variables in this study were operationalized as follows:

- Income (Independent variable): This was measured using a categorical scale, allowing participants to select their monthly income from a predefined set of ranges. This variable was then treated as a continuous measure for the purpose of regression analysis.
- Attitude, Motivation, and Awareness (Dependent Variables): These were treated as composite scores, calculated by averaging the responses to multiple statements on a Likert scale. Each statement was designed to capture a specific facet of the variable it represented. For example, statements on awareness pertained to the understanding of CIBIL's score and the factors affecting a credit score.

Data Analysis

The collected data was processed and analysed using SPSS statistical software. The following statistical techniques were applied:

- **Descriptive statistics**: To summarize the central tendencies and dispersion of the data, including the mean, standard deviation, minimum, and maximum values of all key variables.

- **Correlation Analysis:** Person's correlation coefficient was computed to assess the strength and direction of the linear relationships between the variables.
- **Regression Analysis**: Multiple linear regression models were constructed to determine the predictive power of income on attitude, motivation, and awareness. This method was crucial for testing the study's hypothesis by identifying whether income is a statistically significant predictor of the dependent variables.

The analysis was conducted at a **5% level of significance** (a= 0.05). All statistical tests were two -tailed. Diagnostic checks, including an examination of a multicollinearity through VIF values and the normality and homoscedastic of residuals, were performed to ensure the validity and reliability of the regression model.

Objectives

- To determine if income level significantly influences consumer attitude towards credit scores.
- To examine if income level significantly influences consumer motivation regarding credit score management.
- To ascertain if **income level** significantly influences consumer **awareness** of CIBIL score mechanisms.

Hypothesis

Ho: There's no statistically significant influence of income level on consumer attitude towards credit score.

Ho: There's no statistically significant influence of income level on consumer motivation regarding credit score management.

Ho: There's no statistically significant influence of income level on consumer awareness of CIBIL score mechanism.

Data Analysis and Interpretation

Regression Analysis for Variable Attitude

Descriptive Statistics			
	Mean	**Std. Deviation**	**N**
Mean Attitude	3.237778	.5857068	150
Income	3.91	1.416	150

Interpretation: Participants, on average, had a **moderate attitude** (mean ≈ 3.24) toward CIBIL score awareness. The average **income level was 3.91**, with some variation among participants.

Correlations			
		Mean Attitude	**Income**
Pearson Correlation	Mean Attitude	1.000	.086
	Income	.086	1.000
Sig. (1-tailed)	Mean Attitude	.	.148
	Income	.148	.
N	Mean Attitude	150	150
	Income	150	150

Interpretation: There is a **very weak positive correlation** (r = 0.086) between income and attitude, which is **not statistically significant** (p = 0.148).

Model Summary									
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**				
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**
1	.086[a]	.007	.001	.5855175	.007	1.096	1	148	.297
a. Predictors: (Constant), Income									

Interpretation: Income explains **less than 1%** (R^2 = 0.007) of the variance in attitude. The model has a **very low predictive power**.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.376	1	.376	1.096	.297[b]
	Residual	50.739	148	.343		
	Total	51.115	149			
a. Dependent Variable: Mean Attitude						
b. Predictors: (Constant), Income						

Interpretation: The **regression model is not statistically significant** (F(1,148) = 1.096, p = 0.297). Thus, income does **not significantly predict** attitude.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.099	.141		22.023	.000		
	Income	.035	.034	.086	1.047	.297	1.000	1.000
a. Dependent Variable: Mean Attitude								

Coefficient Correlations[a]			
Model			Income
1	Correlations	Income	1.000
	Covariances	Income	.001
a. Dependent Variable: Mean Attitude			

Interpretation:

- The correlation of Income with itself is **1.000** — this is expected because any variable is perfectly correlated with itself.
- The **covariance** value of **0.001** reflects the variance shared between the income variable and itself (also expected in single-variable regression).
- This table is typically more informative when there are **multiple independent variables**, as it helps detect multicollinearity between predictors. In your case (only one predictor), it's just a default output with no actionable insight.

Collinearity Diagnostics[a]					
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	Income
1	1	1.941	1.000	.03	.03
	2	.059	5.712	.97	.97
a. Dependent Variable: Mean Attitude					

Interpretation:

- **Eigenvalues** close to 0 and **high Condition Index values (usually >30)** suggest collinearity.
- In this model:
  - Lowest eigenvalue is **0.059** (not too small)
  - Highest condition index is **5.712**, which is **well below the threshold of concern (30)**

Regression Analysis for Variable Motivation

Descriptive Statistics			
	Mean	Std. Deviation	N
Mean Motivation	2.822222	.5941131	150
Income	3.91	1.416	150

Interpretation: The average level of motivation among respondents is **moderate (mean = 2.82)** with a small standard deviation. Income levels show more variation, indicating diversity in economic status.

Correlations			
		Mean Motivation	Income
Pearson Correlation	Mean Motivation	1.000	.023
	Income	.023	1.000
Sig. (1-tailed)	Mean Motivation	.	.391
	Income	.391	.
N	Mean Motivation	150	150
	Income	150	150

Interpretation: There is a **very weak positive correlation** (r = 0.023) between income and motivation, and it is **not statistically significant** (p = 0.391). This means income is not linearly related to motivation in this sample.

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.023[a]	.001	-.006	.5959634	.001	.076	1	148	.783
a. Predictors: (Constant), Income									

Interpretation: The R^2 value (0.001) shows that income explains **only 0.1% of the variance** in motivation. The **adjusted R^2 is negative**, indicating the model is **worse than just using the mean** as a predictor. This confirms a very poor model fit.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.027	1	.027	.076	.783[b]
	Residual	52.566	148	.355		
	Total	52.593	149			
a. Dependent Variable: Mean Motivation						
b. Predictors: (Constant), Income						

Interpretation: The regression model is **not statistically significant** ($F(1,148) = 0.076$, **p = 0.783**). This confirms that income does not meaningfully explain variance in motivation.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.785	.143		19.444	.000		
	Income	.010	.034	.023	.276	.783	1.000	1.000
a. Dependent Variable: Mean Motivation								

Interpretation:

- The **unstandardized coefficient** for Income is 0.010, which implies a **very small increase** in motivation with income, but the **relationship is not significant** (p = 0.783).
- The **VIF = 1.000** and **Tolerance = 1.000** indicate **no multicollinearity**, which is expected in a single-predictor model.

Coefficient Correlations[a]			
Model			Income
1	Correlations	Income	1.000
	Covariances	Income	.001
a. Dependent Variable: Mean Motivation			

Interpretation: Since Income is the only independent variable, it is perfectly correlated with itself (1.000), and the **covariance is 0.001** — which is normal in such a case.

Collinearity Diagnostics[a]					
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	Income
1	1	1.941	1.000	.03	.03
	2	.059	5.712	.97	.97
a. Dependent Variable: Mean Motivation					

Interpretation:

- The **Condition Index** of **5.712** is **well below the critical threshold of 30**, indicating **no signs of collinearity issues**.
- The **variance proportions** further confirm that both constant and income are contributing uniquely to the model.

Regression Analysis for Variable Awareness

Descriptive Statistics			
	Mean	Std. Deviation	N
Mean Awareness	3.3867	.71336	150
Income	3.91	1.416	150

Interpretation: The average awareness level is **moderate (Mean = 3.39)** with some spread in responses. Income values show more variability, indicating diversity in the sample.

Correlations			
		Mean Awareness	Income
Pearson Correlation	Mean Awareness	1.000	.131
	Income	.131	1.000
Sig. (1-tailed)	Mean Awareness	.	.056
	Income	.056	.
N	Mean Awareness	150	150
	Income	150	150

Interpretation:

- There is a **weak positive correlation (r = 0.131)** between income and CIBIL awareness.
- The p-value (0.056) is **very close to significance** at the 0.05 level but still **not statistically significant**. It **suggests a possible trend**, but not a confirmed relationship.

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.131[a]	.017	.010	.70963	.017	2.571	1	148	.111
a. Predictors: (Constant), Income									

Interpretation:

- The model explains **1.7% of the variance** in awareness.
- This is a **weak model**, though slightly better than the models for attitude and motivation.
- **Adjusted R^2 = 0.010** indicates a small true explanatory power.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.294	1	1.294	2.571	.111[b]
	Residual	74.529	148	.504		
	Total	75.823	149			
a. Dependent Variable: Mean Awareness						
b. Predictors: (Constant), Income						

Interpretation:

- The model is **not statistically significant** (p = 0.111).
- While the F-value (2.571) is higher than in previous models, it's **still not enough** to prove that income significantly predicts awareness.

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.129	.171		18.349	.000		
	Income	.066	.041	.131	1.603	.111	1.000	1.000
a. Dependent Variable: Mean Awareness								

Interpretation:

- The unstandardized coefficient (B = 0.066) suggests that for every 1 unit increase in income, awareness increases by 0.066 points.
- However, the **p-value = 0.111** means this is **not statistically significant**.
- There are **no multicollinearity issues** (VIF = 1.000, Tolerance = 1.000).

Coefficient Correlations[a]			
Model			Income
1	Correlations	Income	1.000
	Covariances	Income	.002
a. Dependent Variable: Mean Awareness			

Interpretation: This is standard output — Income is perfectly correlated with itself, and covariance is small. It becomes more useful in multi-variable models.

Collinearity Diagnostics[a]					
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	Income
1	1	1.941	1.000	.03	.03
	2	.059	5.712	.97	.97
a. Dependent Variable: Mean Awareness					

Interpretation:

- The **Condition Index of 5.712** is **well below** the critical threshold of 30.
- This confirms **no multicollinearity or instability** in the regression estimation.

Hypothesis Results

- Hypothesis1: (Ho) There's no statistically significant influence of income level on consumer attitude towards credit score.

Result: The regression analysis non-statistically significant value ie. (p=0.297) so Null Hypothesis is **not rejected**.

- (Ho) There's no statistically significant influence of income level on consumer motivation regarding credit score management.

Result: The regression analysis non-statistically significant value ie. (p=0.707) so Null Hypothesis is **not rejected**.

- (Ho) There's no statistically significant influence of income level on consumer awareness of CIBIL score mechanism.

Result: The regression analysis non-statistically significant value ie. (p=0.111) so Null Hypothesis is **not rejected**.

Conclusion and Discussion

Conclusion

This research aimed to systematically investigate the impact of income on consumers' attitude, motivation and awareness concerning CIBIL scores. Utilizing descriptive statistics, correlation analysis, and multiple linear regression, the study analyzed the data from 150 participants. The finding consistently indicates the **INCOME level does not serve as a statistically significant predictor** of an individual's attitude towards credit scores, their motivation to manage them, or their general awareness of CIBIL.

Specifically, the regression models for Attitude, Motivation, and Awareness, with income as the sole predictor, yielded very low R-squared values and non-significant F-statistics. Furthermore, the individual regression coefficients for income across all three models were not statistically significant. While weak positive correlations were observed between income and these variables, they did not reach the threshold for statistical significance. This suggests that, within the scope and limitations of this study, variations in income do not explain a meaningful portion of the variance in consumers' attitudes, motivations, or awareness regarding credit scores.

Discussion

The results of this study present a compelling counterpoint to the intuitive assumption that higher income directly translates to greater financial engagement, more positive attitudes, and enhanced awareness regarding complex financial tools like credit scores. The consistent ack of statistical significance across all analyses for income's predictive power on attitude, motivation, and awareness suggests that these psychological and cognitive constructs may be influenced by factors beyond mere financial capacity.

One possible explanation for these findings is that **financial literacy and awareness are not solely a function of income.** Individuals across various income brackets may gain financial knowledge through diverse channels, such as formal education, personal experiences, peer interactions, or targeted financial literacy programs. It is possible that access to information and a general understanding of financial principles are becoming more democratized, lessening the direct impact of income as a primary determinant. For an instance, a person with low-income will actively seek to improve their financial standing might exhibit higher motivation and awareness than that pf a person with high-income who takes their financial health for granted.

Moreover, the **psychological dimensions of attitude and motivation** might be driven more by intrinsic factors, personal values, and life goals rather than solely by the mount of money earned. An individual's proactive approach to financial management, including credit scores could stem from a desire of financial independence, a fear of debt, or a commitment to long-term planning, irrespective of their current earnings.

The strong and significant correlation observed among Attitude, Motivation and Awareness. This implies that fostering a positive attitude might concurrently enhance motivation and awareness, and vice-versa, regardless of holistic financial education approaches.

From a practical standpoint, these findings carry significant implications for policymakers and financial institutions. If income is not a key differentiator for attitude, motivation, or awareness, then **financial literacy and credit awareness initiatives should adopt a universal design,** aiming to reach a broad audience rather than being exclusively tailored or prioritized for specific income segments. Resource allocated to improving credit understanding might be more effectively utilized through widespread public campaigns, accessible digital platforms, and educational modules integrated into various community programs rather than focusing on income-based targeting.

Limitations and Future Scope

Limitations

- **Cross-sectional Design:** The study's cross-sectional nature limits the ability to infer causality. The observed relationships are associated at a single point in time, and it is not possible to determine if changes in income cause changes in attitude, motivation, or awareness or vice versa.
- **Simple Characteristics:** The study was conducted with a specific sample of participants, and the generalizability of these findings to the broader Indian population or other demographics might be limited. The income ranges used might also not capture the full spectrum of economic diversity.
- **Operationalization of Variables:** While composite scores were created, the nuances of complex psychological constructs like "Attitude" and "Motivation" might not be fully captured by a limited set of survey questions.
- **Omitted Variable Bias:** The models did not include other potentially significant predictors that could influence attitude, motivation, and awareness, such as prior financial education, personal experiences with dept or credit, family financial background, access to financial advisors, or

psychological traits like risk aversion or self-efficacy. The unexplained variance (high residual sums of squares) that other factors are at play.

Future Scope

- **Longitudinal Studies:** Future research could employ longitudinal designs to track changes in attitude, motivation, and awareness over time in relation to income fluctuations or other life events, thereby allowing for stronger inferences about causality.
- **Inclusion of Additional Predictors:** Expanding the set of independent variables to include other socio-economic factors like occupation, area of residence etcetera, psychological traits, and behavioral aspects like frequency of financial planning and investment habits, could provide a more comprehensive understanding of the determinants of financial attitude, motivation, and awareness.
- **Qualitative Research:** Incorporating qualitative methods, such as in-depth interviewsor focus groups, could offer richer insights into the underlying reasons why individuals hold certain attitudes, are motivated or not, and how they acquire financial awareness, complementing the quantitative findings.
- **Targeted Interventions and Experimental Designs:** Future studies could design and evaluate the effectiveness of specific financial literacy interventions across different income groups to see if tailored approaches yield better results, even if income isn't a direct predictor of initial levels.
- **Comparative Studies:** Conducting comparative studies across different regions, socio-economic strata, or even countries could highlight cultural factors that influence these relationships, providing broader generalizability.
- **Advanced Economic Models:** Exploring more complex econometric models that account for potential non-linear relationships or interaction effects between variables could uncover more subtle influences that linear models might miss.

By addressing these limitations and pursuing the suggested avenues< future research can build upon these findings to develop a more nuanced and robust understanding of consumer financial behavior in relation to credit scores, ultimately fostering more effective financial empowerment initiatives.

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