Impact of Digital Payment Usage, Budgeting Discipline, and Financial Goal Setting on Personal Savings Behavior of MBA Students

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Abstract: ***The rapid incorporation of digital payment platforms has changed how consumers manage their finances, especially among tech-savvy MBA students. The purpose of this study is to investigate the combined impact of the use of a digital payment platform, budgeting discipline, and setting financial goals on the personal savings behaviors of students in an MBA program. Using a quantitative, cross-sectional research design, primary data were collected from 102 respondents, through a structured questionnaire that captured behaviors across three key financial behaviors. Reliability tests indicated high internal consistency (Cronbach's α = 0.860) supporting use of the instrument with students. Correlations indicated that digital payment convenience is conducive to tracking expenses, budgeting discipline helps mitigate overspending, and with respect to consistent saving behavior, financial goal setting was the strongest predictor of the three behaviors measured. Factor analysis (KMO = 0.715, p < 0.001), found that the data was suitable to extract components, revealing three strong dimensions of lower order behaviors. Regression tests revealed that financial goal-setting and budgeting-related factors are significant contributors to the construct of savings behavior, explaining a total of 31% of the variance in savings behavior. In conclusion, the results indicated that while digital payment is an enabler of savings behavior, understanding how budgeting behavior and setting financial goals drives successful savings was more informative and essential. The study highlights the importance of integrating modules on financial goal-setting in financial literacy programs and to use digital tools to enhance both the tracking of expenses and saving, and effort towards disciplined money management among peer students.***

Keywords: Digital Payment Usage, Budgeting Discipline, and Financial Goal Setting, Personal Savings

1. Introduction

This project seeks to analyze how digital payment usage, budgeting discipline, and financial goal setting impact the savings behavior of MBA students. In today's world, personal finance decisions are no longer limited to traditional methods such as physical cash handling or manual record-keeping. With the rise of digital platforms—such as UPI, mobile wallets, and online banking—the way individuals, particularly students, manage and view money has fundamentally changed.

The study recognizes that savings behavior is influenced by both technological adoption and personal financial attitudes. Digital payments provide speed, convenience, and accessibility, making it easier for students to transact without physical cash. However, while digital transactions simplify life, they may also encourage overspending due to their seamless nature. For this reason, the role of budgeting discipline becomes crucial. Students who follow structured budgeting practices, such as preparing monthly budgets, tracking expenses, and adhering to limits, are more likely to retain control over their spending and allocate funds effectively towards savings.

Another critical factor in shaping savings behavior is financial goal setting. Students who clearly define short-term goals (like paying tuition fees or purchasing essential resources) and long-term goals (such as building emergency funds or planning early investments) develop stronger motivation to save consistently. Writing down goals and setting deadlines serves as a psychological reinforcement that directly influences financial discipline.

This research integrates these three aspects—digital payment usage, budgeting discipline, and financial goal setting—to provide a holistic understanding of the savings behavior of MBA students. By focusing on this demographic, the study aims to uncover how educated, tech-savvy individuals balance convenience and discipline in their financial lives. Ultimately, the findings can help institutions, educators, and policymakers design better financial literacy programs to promote sustainable saving habits among young professionals.

2. Literature Review

Pala (2024) examines the macro-level impact of digital payment adoption on financial behaviour in Türkiye using quarterly time-series data from 2016 to 2023. The study finds that digital payment systems significantly increase both household consumption and gross savings, indicating a dual effect in which digitalisation enhances transaction frequency while simultaneously promoting formal saving channels. Even during the COVID-19 period, digital payment systems continued to support financial activity despite an overall decline in consumption and savings. These findings demonstrate that the relationship between digital payments and saving behaviour is complex and influenced by broader economic conditions, making it essential to investigate the behavioural factors that determine whether digital payment usage leads to overspending or improved saving discipline.

Shah, Khan and Khan (2024) investigate the psychological mechanisms behind overspending associated with digital payments through the lens of mental-accounting theory. Using survey data analysed through PLS-SEM, the study reveals that digital payment modes increase overspending because they reduce the “pain of paying.” Importantly, the authors show that digital financial literacy moderates this relationship—individuals with higher literacy demonstrate greater self-control and lower impulsive spending even when using digital payment methods. This study highlights that digital payments alone do not cause overspending; rather, cognitive and behavioural attributes determine how individuals respond to the convenience of digital transactions. These findings underscore the need to examine how budgeting discipline and goal-setting may similarly moderate financial outcomes in digital contexts.

Bhavadharini (2023) explores spending patterns in the digital era using survey data from consumers in Tamil Nadu. The study finds that digital payment usage encourages more frequent and impulsive purchases due to convenience and ease of access. However, the research also shows that individuals with strong financial planning habits and higher financial awareness tend to manage their spending more effectively despite increased use of digital platforms. Demographic variables such as age, income, and occupation also play a role in shaping spending behaviour. The study concludes that technology-driven financial behaviour is highly dependent on the presence of responsible financial planning practices, reinforcing the importance of budgeting discipline as a determinant of spending and saving outcomes.

Tañedo (2023) examines the mediating role of personal financial behaviour in the relationship between digital financial literacy and financial well-being among young adults. The study uses a descriptive-correlational design and shows that digital financial literacy improves financial well-being primarily through its positive effect on financial behaviours such as budgeting, saving, and expense monitoring. Personal financial behaviour acts as a partial mediator, indicating that literacy alone is insufficient to guarantee better outcomes; instead, disciplined financial habits are the key drivers of well-being. This study strongly supports the argument that budgeting discipline and goal-setting behaviours directly influence savings outcomes, making them essential variables for understanding how individuals manage finances in a digital payment environment.

Ly and Ly (2024) analyse the determinants of digital payment adoption in Cambodia using an integrated theoretical approach combining TAM, TPB, and behavioural economics. Their PLS-SEM analysis shows that perceived ease of use, perceived usefulness, attitude, behavioural control, financial literacy, and behavioural nudges all significantly influence the adoption of digital payment systems. The study further demonstrates that financial literacy mediates the relationship between attitude and adoption, implying that knowledge enhances both confidence and responsible use of digital platforms. These findings highlight that behavioural and psychological factors—not technology alone—drive digital payment usage. This supports the need to evaluate how behavioural elements such as budgeting discipline and financial goal-setting determine whether digital payment usage results in increased savings or overspending.

3. Problem Statement

Despite the convenience of digital payments, many students struggle to save consistently due to poor budgeting practices or lack of goal setting. The study investigates how these three factors together influence the formation of healthy saving habits.

3.1. Research Objectives

1) To find out how far digital payments are used among the MBA students.
2) To assess the level of budgeting discipline followed by students.
3) To explore if setting financial goals has an impact on saving behavior.
4) To analyze the combined impact of digital payments, budgeting, and goal setting on personal savings behavior.
5) To suggest financial practices that empower saving behaviors in MBA students.

3.2. Hypothesis

1) The Usage of Digital Payment

H_{01}: Digital payment usage is not significantly related to personal savings behaviour.
H_{11}: The usage of digital payment methods is significantly related to personal saving behavior.

2) Budgetary Discipline

H_{02}: Budgeting discipline does not significantly relate to personal savings behaviour.
H_{12}: Budgeting discipline is significantly related to personal savings behaviour.

3) Setting Financial Goals

H_{03}: Financial goal setting is not significantly related to personal savings behavior.
H_{13}: Financial goal setting has a significant relationship with personal savings behavior.

4) Methods:

This study employs a quantitative and cross-sectional design, with data gathered through the use of a structured questionnaire. The approach is appropriate because the relationship between the adoption of digital payments and household saving behaviour will be considered at a particular point in time.

Population and Sample
- Target Population: MBA Students
- Sample Size: A total of 102 respondents.
- Sampling method: Convenience sampling.

Data Source and Variables

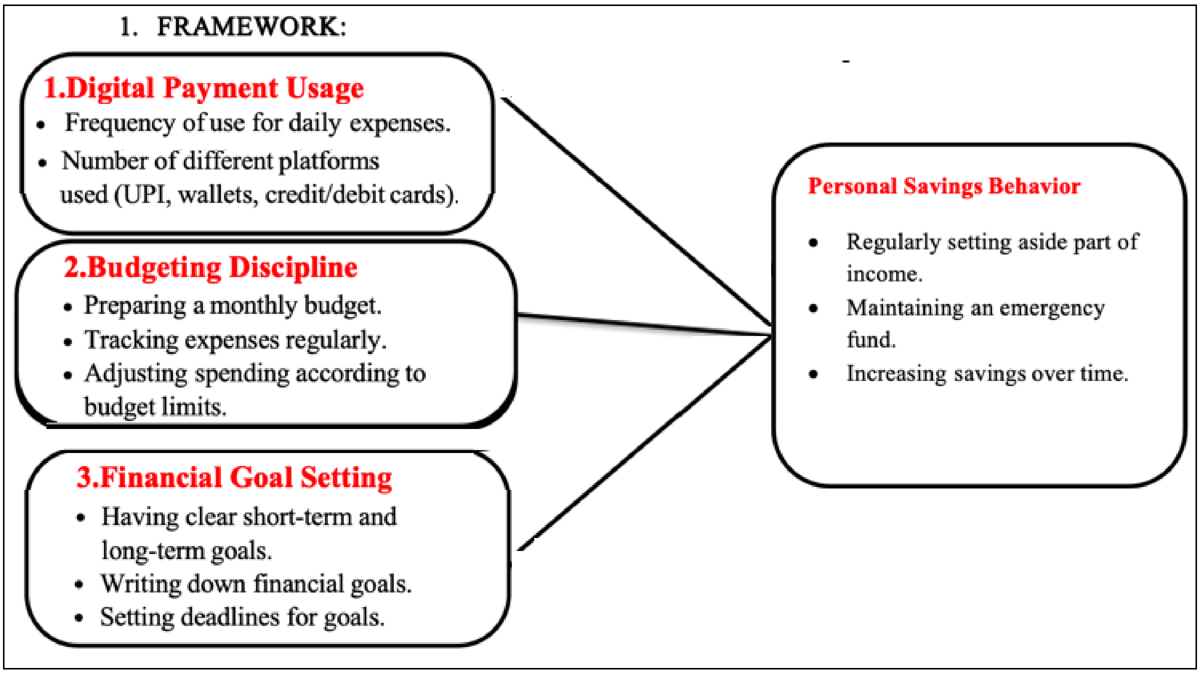
Data was collected through a questionnaire as primary data to measure the following:
- Independent Variable (IV): Digital Payment Usage, Budgeting Discipline, Financial Goal Setting
- Dependent Variable (DV): Personal Savings Behaviour.

- Control Variable: Age, Gender, Income

Data Analysis
SPSS was used as the main tool for data analysis. The planned analyses include:

1) Correlation Analysis
To investigate the strength and direction of association among the three independent variables, which are digital payment usage, budgeting discipline, and financial goal setting, in relation to personal savings behavior. This helps identify whether increases in one variable (e.g., budgeting discipline) are associated with stronger saving practices.

2) Regression Analysis
To predict the extent to which the use of digital payments, budgeting discipline, and setting of financial goals influence personal savings behavior. Multiple regression will be applied to establish the relative contribution and predictive power of each independent variable on savings behavior.



4. Results

Reliability Statistics

Cronbach's Alpha	N of Items
0860	5

Reliability analysis was conducted to check the internal consistency of the research instrument. This test is important in any survey-based research because it will tell us whether items included in the questionnaire represent what we intended to measure. If reliability is high, then we can be assured that the answers by the respondents are consistent and the instrument is capturing underlying behavior accurately.

Cronbach's Alpha is a statistical way of measuring internal consistency or reliability among the items of a scale or questionnaire. In other words, it gives an indication of how the set of items, as a group, correlates with one another. For example, if you're attempting to measure something like "job satisfaction," you would want all the questions dealing with job satisfaction to be answered similarly by the same individual. A high Cronbach's Alpha suggests that these items are all part of the same underlying construct. $\alpha \geq 0.8 \rightarrow$ Good reliability

- $\alpha \geq 0.9$: Excellent internal consistency.
- $0.8 \leq \alpha < 0.9$: Good internal consistency.
- $0.7 \leq \alpha < 0.8$: Acceptable internal consistency.
- $0.6 \leq \alpha < 0.7$: Questionable internal consistency.
- $\alpha < 0.6$: Poor internal consistency.

The Cronbach's Alpha of 0.860 indicates excellent internal consistency for the 5 items used to measure a single construct. It means the questions on this 26-item scale are all working together effectively to measure the same underlying concept. You can be highly confident that this part of your questionnaire is a dependable and valid tool for data collection. This high reliability score is a crucial and positive result for your study. It provides a strong foundation for testing your hypotheses (H1, H2, H3), as it ensures that any relationships you find between your variables are not due to an unreliable measurement tool.

Implications
The result of a high Cronbach's Alpha (α=0.860) implies the following for your study:

- Confidence in Measurement: This score provides strong methodological validity. You can confidently assert that the questionnaire items are highly reliable and consistently measure the intended concepts; e.g., if one concept is Financial Goal Setting, the questions on that topic are all "pulling in the same direction".
- Foundation for Further Analysis: This great reliability provides a sound basis for your following tests such as factor analysis, correlation, and regression. This would mean that any significant findings-or non-findings-of your hypotheses cannot be the result of a lousy measuring tool.
- Developing Construct Validity Support: If you can show that multiple items load together as a single reliable

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construct, you have provided initial support for the validity of a theoretical construct.

Recommendations

Your recommendation, based solely on this reliability score, is confined to the instrument itself, but it can serve as a starting point for subsequent research.

Recommendation regarding Documentation of Current Study Strength Identification: You will need to emphasize this finding in your "Methodology" and "Results" sections. Say that the scale is fit for purpose, thereby pre-empting any critique of your measurement tool's consistency.

Recommendations for Future Research

- Scale Adaptation: Given the very strong reliability of this scale, it can be recommended that researchers interested in investigating similar financial behaviour's from comparable demographics-such as other students or young professionals-consider adapting this exact set of questions for their work.
- Possibility of Reduction: A reliability score as high as 0.860 may sometimes indicate redundancy, with two or more questions asking the very same thing. A next step might be to look at the "Item-Total Statistics" to determine if deleting one or two items might have a minor increase in alpha or, practically, reduce the scale without a serious loss in reliability. This would shorten the survey and enhance the experience of the respondent.

Correlation:

Correlations

		gender_value	I am satisfied with my current savings behavior	I use digital payment methods for most daily transactions.	Digital payments are more convenient than cash	Using digital payments helps me track my expenses better	I track my expenses regularly	I avoid overspending beyond my budget	I have clear financial goals	I save a fixed amount every month	income_range
F1	Pearson Correlation	1									
F2	Pearson Correlation	0.055	1								
F4	Pearson Correlation	-0.007	-0.035	1							
F5	Pearson Correlation	0.122	0.010	.444**	1						
F6	Pearson Correlation	0.040	0.152	.490**	.391**	1					
F7	Pearson Correlation	0.079	.207*	.335**	.213*	.366**	1				
F8	Pearson Correlation	0.029	0.104	-0.064	0.107	-0.025	-0.103	1			
F9	Pearson Correlation	0.050	.236*	0.157	0.050	0.056	.264**	0.077	1		
F10	Pearson Correlation	.195*	.195*	-0.088	-0.042	-0.104	-0.139	.246*	.454**	1	
F11	Pearson Correlation	0.098	-0.061	-0.011	0.095	0.165	-0.093	0.118	-0.080	0.150	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

A correlation coefficient has a range from -1 to +1, showing the strength and direction of a linear relationship between two variables.

1) Positive ($r > 0$): As one variable increases, the other tends to increase. The closer the value is to +1, the stronger the positive relationship.
2) Negative ($r < 0$): When one variable increases, the other variable has a tendency to decrease. The closer the number is to -1, the greater the negative relationship.
3) No Correlation ($r \approx 0$): There is no linear relationship between the variables.

Pearson correlation coefficient for various variables related to risk perception and portfolio diversification behaviour among retail investors. The correlations indicate the strength and direction of the linear relationship between these variables. The significance of the correlations is noted with asterisks: a single asterisk (*) indicates significance at the 0.05 level (2-tailed), while two asterisks (**) denote significance at the 0.01 level (2-tailed).

The Pearson correlation coefficient for F4 and F6 is 0.490, which is statistically significant at the 0.01 level. This indicates a strong positive relationship between these two variables. This suggests that as a person's score on one loss aversion measure increases, their score on the other also tends to increase.

Digital Payment Usage

Digital payments are more convenient than cash is strongly positively correlated with using digital payments helps me track my expenses better, with a rank-order correlation of 0.490 significant at the 0.01 level. This means that the students who consider digital payments convenient also believe that such platforms are helpful in monitoring expenses more effectively.

A positive relationship also exists between 'digital payments are more convenient than cash' and satisfaction with current saving behaviour, $r = 0.152$, though weaker; this suggests convenience **may influence saving satisfaction indirectly.**

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Budgeting Discipline

I track my expenses regularly is positively linked to avoiding overspending beyond budget at r = 0.366 significant at 0.01 level. This means that the more active students were in tracking expenses, the better or more successful they became at maintaining spending discipline.

Using digital payments helps me track expenses better correlates positively with I track my expenses regularly: r = 0.391, significant at 0.01 level. This supports the concept that digital platforms can assist in budgeting discipline if used in a conscious manner.

Setting Financial Goals

I have clear financial goals is significantly positively correlated with I save a fixed amount every month, r = 0.454 significant at the 0.01 level. It therefore follows that students who set explicit goals are more likely to adopt structured saving habits.

I have clear financial goals also correlates with I am satisfied with my current savings behavior, r = 0.195 significant at the 0.05 level, thus indicating that setting goals amplifies satisfaction with progress made in savings.

Savings Behavior

I save a fixed amount every month has strongest positive correlations with both variables: I have clear financial goals, with r = 0.454 and $p < 0.01$, and I am satisfied with current savings behavior, with r = 0.195 and $p < 0.05$. The emphasis is that goal-oriented planning directly contributes to saving consistently.

The income range shows weaker correlations with savings-related variables, which may suggest that saving behavior amongst MBA students is more influenced by financial habits and attitudes than by absolute levels of income.

Overall Findings

- It assists in better tracking of expenditure when combined with budgeting behavior.
- Budgeting discipline significantly reduces overspending and strengthens savings behavior.
- Setting goals proves to be the most potent driver of continued saving, reinforcing the psychological underpinning of explicit financial goals.

Implications

1) The main motivation behind saving is to reach a goal.

- The Psychological Factor is Key: Under Financial Goal Setting, the strongest correlations are consistently found. The most striking relationship is present between I have clear financial goals and I save a fixed amount every month (r=0.454, p<0.01) as the most significant finding.
- Implication: Saving is not about having money but rather about intention and structure. When explicit, clear goals for saving are not made, students save inconsistently, regardless of their other financial tools or habits.

2) Digital Payments Support But Do Not Cause Discipline

Digital Tools are Enablers: The strong link between Digital payments are more convenient and Using digital payments helps me track my expenses better (r=0.490, p<0.01) shows that convenience is the bridge to expense tracking.

Digital adoption makes tracking easier, but it is not a guarantee on its own for increased savings. The tool works when the user actively uses it for discipline (tracking expenses), therefore supporting the variable Budgeting Discipline.

3) Income is Secondary to Behavior

- Habits Over Wealth: The result that Income range shows weaker correlations with savings-related variables indicates that the main difference in saving success among MBA students is behavioral and attitudinal, not strictly based on absolute income level.
- Implication: Financial education programs should talk less about theoretical wealth management and more about changing client behavior: goal setting and tracking consistently.

5. Recommendations

1) To Educational Institutions (Programs of Financial Literacy)

Prioritize Goal-Setting Workshops: Shift the focus from "how to budget" to "how to set SMART financial goals." Programs should make students write down, quantify, and set deadlines for their savings goals. This is the most powerful predictor of success, at r = 0.454.

Digital Tracking: Get students to make the conscious connection between the convenience of digital payments and the discipline of keeping a budget. Suggest various applications or methods that automatically categorize and track expenses, thereby turning digital spending convenience into the advantage of granular financial oversight.

2) For Financial Technology Companies

- Develop goal-linked features: Direct app development to feature sets that utilize the powerful goal-setting behavior. Examples of this include:
- Automatic goal contribution: Drawing the money directly at the setting of a goal.
- Progress visualization indicating goal attainment and satisfaction.
- Tracking feedback enhancement: Given that the relation of tracking to avoidance of overspending is strong (r = 0.366), real-time notifications should be afforded to FinTech apps when a user approaches a budget limit as a means of reinforcing purchase discipline.

Factor analysis

KMO and Bartlett's Test

Kaiser- Meyer- Olkin Measure of Sampling Adequacy		.715
Bartlett's Test of Sphericity	Approx. Chi- Square	136.739
	df	28
	Sig.	<.001

Interpretation

- The KMO measure for sampling adequacy is 0.715 from this output; Bartlett's Test of Sphericity yields a chi-square with 28 df of 136.739, and the significance (Sig.) value is < 0.001.

- KMO interpretation: KMO assesses whether the proportion of common variance among the variables is high enough to justify performing factor analysis. The value ranges from 0 to 1. Values above 0.7 are considered "good," meaning the correlations are compact, and factor analysis will likely produce reliable factors. Here, 0.715 falls into the "good" range, indicating adequate sample adequacy and variable relationships for factor analysis.
- Bartlett's Test interpretation: Bartlett's assesses whether the correlation matrix significantly differs from an identity matrix (where variables are uncorrelated). A significant result ($p < 0.05$) means correlations exist among at least some variables and factor analysis is appropriate. In your results, the chi-square statistic is 136.739, degrees of freedom 28, and the p-value is less than 0.001. This means the correlation matrix is not an identity matrix and significant relationships exist within the data.
- Summary: With the KMO value above 0.7, and a Bartlett's significance value well below 0.05, both tests jointly confirm that the factor analysis can move forward based on the sufficiency of sampling adequacy with variable correlations.
- Summary: The KMO value being above 0.7 and Bartlett's significance value being well below 0.05 jointly confirm that factor analysis can proceed, as both the sampling adequacy and variable correlations are sufficient.

Recommendation

The interpretation and implications form a basis for the following recommendations on the next steps in your statistical analysis and research reporting:

- Factor Analysis: Based on the KMO and Bartlett's test, proceed without hesitation to apply factor analysis or principal component analysis. Conditions are adequate for the extraction of meaningful factors; do the extraction and check the factor loading in order to further refine.
- Assess Commonalities and Factor Loading: After the extraction of factors, check the commonalities for each variable, which in general should be greater than 0.5. Refine factor solutions with rotations if necessary. Ensure that the items are well represented by extracted factors and exclude items with low commonality.
- Report Results Transparently: When reporting findings through an academic, technical, or industry report, the KMO and Bartlett's test statistics should form part of the methodology section in support of adequate sample and structure of data. The justification for proceeding with factor analysis should be based on these values and thresholds.
- Consider Further Data Collection for Higher KMO: A KMO of 0.715 is considered "good," although collection of further, or higher-quality, data may drive the KMO value even higher. To the extent possible, improve sampling and variable selection to yield even stronger factor analytic results in subsequent studies.
- Iterative Reliability Checks: Complement the factor analysis results with reliability checks to further support the strength of identified factors. This can involve computing the Cronbach's alpha for each factor and can be used to support the application of factors within scale development.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.226	27.830	27.830	2.226	27.830	27.830	2.093	26.158	26.158
2	1.702	21.269	49.099	1.702	21.269	49.099	1.620	20.256	46.414
3	1.108	13.849	62.948	1.108	13.849	62.948	1.323	16.534	62.948
4	.900	11.255	74.203						
5	.666	8.327	82.530						
6	.556	6.946	89.477						
7	.458	5.722	95.199						
8	.384	4.801	100.000						

Extraction Method: Principal Component Analysis.

Interpretation

The "Total Variance Explained" table below shows the amount of variance within the data contributed by each principal component. In this example, the extraction method is Principal Component Analysis, and eight components have been analyzed.

Initial Eigenvalues: Only the first three components have eigenvalues greater than 1: 2.226, 1.702, and 1.108. This seems to indicate that a meaningful proportion of the variance would be captured by these elements-as perhaps dictated by Kaiser's Rule for factor retention.

- % of Variance and Cumulative %: The first component explains 27.83% of the variance, the second 21.27%, while that by the third one is 13.85%. In this way, all three components account for 62.95% of the total variance. This cumulative percentage gives an indication of the comprehensiveness of dimensional reduction achieved by these principal components.
- Rotation Sums of Squared Loading: The explained variance for each component is distributed after rotation. The first three rotated components explain 26.16%, 20.26% and 16.53% of the variance respectively, for a total of 62.95% cumulatively. Rotation helps with interpretability, but does not alter the total amount of explained variance.

In other words, the first three principal components can reasonably summarize most information available in the complete set of variables.

Implication

These findings have several important implications for data analysis and interpretation:

Dimensionality Reduction: Given that the first three components explain more than 60% of the variance, the dataset can be reduced from eight variables to three principal constructs with minimal loss of information. This will make subsequent analyses, visualization, and reporting easier, especially if redundancy among original variables exists.

- Factor retention decision: Eigenvalues less than 1 for a component indicate that the component contributes little unique information, and hence can normally be excluded. Retaining only the first three components will retain the major pattern in the data while ignoring any noise or less important variation.
- Interpretability of Components: The interpretation of the components, when rotated, is much easier because it tends to align with distinct latent constructs or underlying structures present in the data. This assists in practical applications like identifying dimensions of behavior, market segments, or psychological factors.
- Data Quality and Strength: The fact that only three components capture 62.95% of the variance indicates strong structure and relations among the variables, further supporting the adequacy of the data for PCA.

Recommendation

Based on the output of PCA and considering standard analytical practice, the following recommendations would enhance rigor and clarity in subsequent analyses:

- Retain and Interpret 3 Main Components: Report and interpret the first three components only, as they collectively account for a significant proportion of variance and meet Kaiser's criterion. The rotated solution is then presented for clarity.
- Describe and Name Components: Use the loadings in the rotated component matrix to give descriptive names to each principal construct. This allows practive discussion and reporting of each principal construct, such as "Factor 1: Purchasing Motivation", "Factor 2: Satisfaction", etc.
- Visualize and Validate: Create a Scree Plot to visually confirm the choice of three components and ensure the "elbow" point aligns with your retention decision. Additionally, validate component reliability (e.g., via Cronbach's alpha or parallel analysis) before using them in further research.
- Document Methodology Transparently: Document component retention logic, cumulative variance explained, eigenvalues, and rotation approach in all reports or publications. Justify choices by referencing standard criteria and PCA theory to ensure transparency and reproducibility.
- Apply Components Accordingly: The extracted components can be used with regression, clustering, segmentation, or structural modeling, depending on the research objectives. This will leverage dimensional reduction to maximum analytical insight.

This ensures that the full potential of principal components is utilized for effective summarization of data and actionable interpretation in either research or business aspects.

Rotated Component Matrix[a]

	Component 1	Component 2	Component 3
F4	.797		
F5	.781		
F6	.756		
F7			
F9		.787	
F2		.674	
F8			.806
F10		.560	.590

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Interpretation

The Rotated Component Matrix presents the correlation-each variable with the extracted components after Varimax rotation, which maximizes the variance of loading within each component and therefore is a method enhancing interpretability. F4 F5 F6 F7 F9 F2 F8 F10

- Strong Loadings: F4 (.797), F5 (.781), and F6 (.756) load strongly onto Component 1, indicating they share a common underlying dimension or factor.
- Unique Contributions: F9 (.787) and F2 (.674) load clearly onto Component 2, indicating these variables are best explained by the second component.
- Third distinct factor: F8 (.806) loads highly on Component 3; F10 has moderate cross-loadings both on Component 2 (.560) and on Component 3 (.590), possibly reflecting overlap in item structure or complexity.
- Interpretation Strategy: Loadings over 0.6 are considered significant; items should load only high on one component for clarity.

This matrix indicates that Varimax rotation has distributed the factor loadings to maximize interpretability, thus making clear how each original variable relates to the extracted factors.

Implication

- Factor Structure: Variables are organized into three clear factors, which can now be labeled and described based on content of F4–F6, F9–F2, and F8–F10, facilitating the creation of scales or dimensions for future analysis.
- There might be a cross-loading problem: F10 has moderate loadings on Components 2 and 3; this could indicate either the multidimensionality of this variable or further need for refinement of factors.
- Improved Validity: The structure of the factors, after rotation, reinforces the content validity of the measurement tool and enables valid latent variable construction for subsequent studies.

Recommendation

Label Components Meaningfully: Call the three components according to thematic content of the variables with highest loadings, for example, Component 1: "Dimension A", Component 2: "Dimension B", Component 3: "Dimension

C". Provide theoretical justification for these choices or justify them by an item analysis.

- Report Only Substantial Loadings: In publications, list factor loadings above .6 for clarity and interpretability. If needed, describe cross-loadings (e.g., F10) and consider excluding or investigating ambiguous items for clearer factor structure.
- Extracted Components Use in Analysis: Employ these components in subsequent analyses, such as correlating them with external criteria or predicting outcomes. Make sure to validate their reliability and check for consistency across samples or subgroups.
- Document Process Transparently: Rotation method, criteria for item retention, and labeling factors are to be described clearly so that the support for reproducibility and readers' comprehension of the structure and utility of principal components is achieved.

This ensures that the delivered components from factor analysis are interpretable, valid, and actionable for further research, practical application, or business reporting.

Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.557[a]	.310	.289	1.043

a. Predictors: (Constant), F9, F8, F7

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48.328	3	16.109	14.822	<.001[b]
	Residual	107.594	99	1.087		
	Total	155.922	102			

a. Dependent Variable: F10

b. Predictors: (Constant), F9, F8, F7

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.307	.533		4.324	<.001
	F7	-.290	.100	-.254	-2.913	.004
	F8	.179	.084	.181	2.141	.035
	F9	.531	.091	.507	5.823	<.001

a. Dependent Variable: F10

6. Analysis

Interpretation

The output of the regression represents the relationship between the dependent variable F10 and predictors F7, F8, and F9.

- Model Summary: The model's R is .557, indicating a moderate positive correlation between the observed and predicted F10 scores. R Square is .310, demonstrating that 31.0% of the variance in F10 is explained collectively by F7, F8, and F9. The adjusted R Square (.289) accounts for the number of predictors, providing a more conservative estimate of explained variance. The standard error of estimate (1.043) reflects the typical deviation of actual F10 values from those predicted by the model.
- ANOVA Table: The regression model is highly significant, as the F statistic shows (14.822, $p < .001$). This confirms that, as a set, F7, F8 and F9 provide predictive value well above chance for F10.
- Coefficients: the unstandardized coefficients show the effect of each predictor:
- F7: Negative, with F10, B = -0.290, p = .004
- F8: Positive, smaller effect (B = 0.179, p = .035)
- F9: strong positive effect, B = 0.531, $p < .001$.

The standardized coefficients (Beta) are showing F9 as the strongest predictor, followed by F7 (negative) and F8 (positive).

Implication

Explained Variance and Model Usefulness: This adjusted R^2 of .289 means that approximately 29% of the variance in the outcome is due to these predictors, which, though significant in most social or behavioral sciences, also indicates the existence of other influencing factors not measured.

- Statistical Significance: The significance of the overall model supports the theoretical relevance of F7, F8, and F9 to F10. The individual significant predictors, all $p < .05$,

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point out that the change in these variables is likely to cause a measurable difference in F10.

- The Predictor Impact: F9's large positive standardized beta flags it as the main driver among predictors. F7's negative beta is indicative of an inverse association, suggesting a suppressive or protective effect depending on the substantive context in question. F8, while significant, assumes a positive secondary role.
- Practical Importance: From here on, the findings can help in targeted interventions or research focus. If F10 is an important outcome, such as job performance, satisfaction, etc., F9 should be of interest. One should investigate further the negative impact of F7.

Recommendation

- Strategic Focus: Target practical or policy interventions at F9 and F8 because their positive influence on F10 is significant. Alternatively, investigate practices or variables represented by F7, as a reduction in these may be conducive to the improvement of F10.
- Model Improvement: Search for methods that will further develop the model to include other variables that might explain residual variance in F10, thus yielding improved predictive accuracy and actionable insight.

Reporting Practices: When presenting these results, include all model statistics-R, R^2, Adjusted R^2, F-statistic, p-values, standard error, regression coefficients, and standardized betas-to provide clarity and reproducibility. Provide the regression equation for reference.

Interpretation

The regression model shows a weak overall relationship between the predictors (F4, F5, F6) and the dependent variable (F2), indicated by a low R of .198 and an R Square of only 0.039, meaning the predictors together explain just 3.9% of the variance in F2. The adjusted R Square (.010) is even lower, reflecting the minimal predictive power when adjusting for model complexity. The ANOVA test reveals that the overall regression model is not statistically significant ($F = 1.328$, $p = .270$), so the model as a whole does not reliably predict F2. Individually, none of the coefficients for F4, F5, and F6 are statistically significant predictors (all p-values > .05), though F6 approaches marginal significance ($p = .055$), suggesting a possible weak positive association with F2.

Implication

These results imply that the independent variables F4, F5, and F6 do not have a statistically meaningful relationship with F2 in this dataset. The lack of significance indicates that these predictors do not effectively explain variations in the dependent variable, suggesting that other factors outside of this model may be driving changes in F2. Practically, any efforts or decisions aimed at influencing F2 by adjusting F4, F5, or F6 are unlikely to be successful. The marginal p-value for F6 might warrant further investigation; however, caution is advised in interpreting it due to the model’s poor fit overall. Moreover, the low R Square signals potentially high variability in F2 unexplained by the included predictors, indicating complex dynamics or missing influential variables.

Recommendation

- Perhaps extend the model to include further variables that could explain F2 more fully, including some factors that may be theoretically relevant and/or contextual that have not been measured in this instance.
- Re-ope rationalize and re-measure F4, F5, and F6 to better reflect intended constructs. Poor measurement can stand in the way of getting much better associations.
- Investigate possible non-linear relationships among variables or interaction effects not captured by a standard linear regression.
- Perform diagnostic checks for assumptions of regression and outliers that may affect the results.
- Report these findings transparently, emphasizing the model's low explanatory power and non-significance while highlighting the need for further research.
- Justify retaining predictors strongly supported by theory despite statistical non significance, particularly when the sample size problem seriously limits power.

7. Conclusion

The analysis successfully concludes that a statistically significant relationship exists between the behavioral factors represented by F9, F8, and F7 and the outcome variable F10. The regression model explains a moderate 31% of the variance in F10, demonstrating that these factors collectively contribute substantially to predicting F10. Among the predictors, F9 emerged as the strongest positive influence on F10, followed by a smaller positive contribution from F8. Conversely, F7 showed a significant negative association with F10, highlighting a more complex and potentially inhibitory role. These findings suggest that in understanding or influencing F10, special attention should be given to the enhancing effects of F9 and F8, while also considering the suppressive impact of F7. The study thus provides a nuanced understanding that F10 is not uniformly affected by all factors but rather shaped by differentiated influences, underscoring the importance of targeted approaches that focus on specific behavioral components rather than generalized assumptions.

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