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Drivers of Cryptocurrency Adoption in Iran: Evidence from the Baluchistan Region

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Abstract

Research Originality: This study explores the key factors influencing the acceptance of cryptocurrencies in Iran, focusing on the under-researched Baluchistan region. In contrast to previous studies focusing on developed or technologically advanced economies, this research explores a socioeconomically disadvantaged region experiencing economic instability and restricted access to formal financial services.

Research Objectives: The main goal of the study is to identify and analyze the key factors influencing cryptocurrency acceptance in this region.

Research Methods: Using data from 200 active cryptocurrency users, we employed exploratory factor analysis followed by multiple regression analysis to identify and test predictive factors.

Empirical Results: The findings reveal six primary drivers: financial constraints, national economic volatility, personality traits, social influences, managerial factors, and trust. Among these, income-related motivations and macroeconomic instability emerged as the strongest predictors of adoption.

Implications: The study contributes to the literature by contextualizing cryptocurrency behavior within a developing country's marginalized setting and provides insights for policymakers to enhance financial inclusion. It also highlights the need for regulatory clarity and user education to support safe and effective participation in digital finance.

Keywords:

acceptance; cryptocurrency; economic instability; social influence

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INTRODUCTION

The proliferation of financial technologies has transformed the structure and dynamics of global economic systems. Among these, digital currencies—particularly cryptocurrencies—have emerged as a significant innovation (Carrick, 2016). Cryptocurrencies utilize cryptographic methods to enable secure transactions and control the issuance of new units, operating as decentralized alternatives to traditional fiat currencies (Gil-Cordero et al., 2020). This decentralization, underpinned by blockchain technology, introduces transparency and immutability to transaction records, fostering greater user trust and reducing reliance on centralized intermediaries (Shehzad et al., 2018). The increasing appeal of cryptocurrencies is driven by both technological advancements and the growing public interest in alternative financial instruments that transcend conventional banking limitations.

Several features differentiate cryptocurrencies from traditional financial systems, such as peer-to-peer transfers, near-instant settlements, reduced transaction costs, and a high degree of user anonymity (Phillips et al., 2019; Burr et al., 2018). Unlike fiat currencies regulated by central banks, cryptocurrencies operate through decentralized networks without a central authority, making them particularly appealing during times of financial instability or distrust in policy. (Kumar & Anandrao, 2019). Furthermore, studies have shown that cryptocurrency adoption can positively affect individual welfare by improving savings mechanisms and consumption smoothing (Murakami & Viswanath-Natraj, 2025).

The launch of Bitcoin in 2009, amid the global financial crisis, marked a watershed moment in digital finance. It demonstrated the feasibility of decentralized monetary systems and laid the groundwork for a new class of digital assets (Calderon, 2018; Kumar & Anandrao, 2019). Since then, the digital currency ecosystem has expanded with the emergence of other tokens such as Ethereum, Ripple, and Litecoin. The market capitalization of cryptocurrencies surged from under $500 million in 2012 to over $782 billion in early 2021, indicating a compound annual growth rate exceeding 150%. Bitcoin experienced an unprecedented increase in value, rising from $7,000 to over $60,000 in 2021, reflecting its dual role as both a speculative asset and a potential store of value (Sun et al., 2021).

As of 2024, the global cryptocurrency market has continued to grow at a notable pace. Revenues are expected to reach $51.5 billion, with a projected compound annual growth rate (CAGR) of 8.62% that could push revenues to $71.7 billion by 2028. User adoption is also accelerating, with penetration anticipated to rise from 10.76% in 2024 to 12.39% in 2028, resulting in an estimated global user base of over 992 million. These statistics underscore the increasing integration of cryptocurrencies into mainstream economic activities.

Nevertheless, adoption remains uneven and faces persistent challenges. Technical vulnerabilities such as hacking, malware, and private key mismanagement continue to undermine trust in digital currencies (Apostolaki, 2017; Krombholz et al., 2016; Folkenstein & Lennon, 2016; Madanchian et al., 2025; Luo et al., 2025). Although

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blockchain itself offers protection against tampering, security risks associated with exchanges and user endpoints remain substantial (Nadeem et al., 2021). In addition, regulatory ambiguity, legal uncertainties, market volatility, and the irreversible nature of transactions hinder broader acceptance (Kumar & Anandrao, 2018). The misuse of blockchain for illicit purposes has also fueled skepticism regarding its legitimacy and long-term viability (Conti, 2018). Financial illiteracy and low risk tolerance among specific user segments further exacerbate vulnerability to market shocks (Hayashi & Routh, 2025).

The increasing effect of cryptocurrencies on global financial ecosystems has inspired extensive research into the factors influencing their adoption. Previous studies have applied behavioral, psychological, and technological models to explain individual and collective decisions. Xia (2022) found that social influence, perceived value, and traceability are significant in Malaysia, with customer satisfaction acting as a mediator. Shahzad et al. (2024) emphasized the roles of awareness, trust, and ease of use in facilitating acceptance, reaffirming the Technology Acceptance Model (TAM) as a suitable framework. Liu (2025) highlighted peer influence and social networks as essential, particularly in volatile markets. Similarly, Jalan (2023) identified interpersonal trust as a key structural factor driving the use of cryptocurrencies.

Despite this growing body of literature, existing studies have primarily focused on developed or technologically advanced economies. As Alzahrani (2019) noted, adoption in developing contexts is often shaped by practical concerns, such as transaction speed, privacy, and perceived investment potential, rather than technological novelty or institutional support. However, most research overlooks how these dynamics operate in economically marginalized or financially excluded populations, where informal economies, social networks, and religious attitudes may significantly influence behavior.

This study addresses that research gap by focusing on Iran's Baluchistan region—a context characterized by economic underdevelopment, limited access to formal financial services, and regulatory ambiguity. Iran's overall engagement with cryptocurrencies has increased dramatically in recent years. As of 2023, approximately 22% of Iranians own cryptocurrencies, while 29% report having used or invested in them. Legal ambiguities persist, with the 2018 directive from the Board of Ministers permitting cryptocurrency mining under license but offering no clear regulatory framework for use in transactions. While cryptocurrencies are not formally prohibited, the lack of clarity in the Monetary and Banking Law has created uncertainty about their legal standing. Nonetheless, Iran's projected cryptocurrency revenue for 2024 is $123.4 million, with user numbers expected to exceed $17.32 million by 2028.

This evolving landscape positions Iran as a critical context for studying cryptocurrency adoption, especially in underserved regions like Baluchistan. The province, despite being the largest in Iran by land area, faces persistent socioeconomic challenges, including infrastructural neglect, low formal financial penetration, and high unemployment. Its economic detachment from national systems, combined with increasing digital access and a youthful demographic, creates a unique environment for decentralized finance.

Understanding how behavioral, economic, and social factors intersect in this context is essential for informing inclusive financial strategies and addressing regional disparities in digital access.

Although cryptocurrency adoption has been examined extensively in global literature, few studies have explored how specific socio-cultural and economic conditions affect adoption in economically marginalized regions. Furthermore, models like TAM and UTAUT often overlook context-specific factors such as income instability, informal peer influence, and religious attitudes that may shape user decisions in such settings. This study contributes to the literature by examining these dimensions in Baluchistan using a two-stage quantitative method: exploratory factor analysis (EFA) followed by regression analysis. The research questions guiding this study are: a) What factors most significantly influence cryptocurrency acceptance in Baluchistan? b) How do income, economic instability, social norms, personality traits, management factors, and trust shape this acceptance?

The novelty of this research lies in its focus on an economically and geographically marginalized region within a politically uncertain environment. In contrast to earlier studies focused on developed economies, this research provides insights from a population that has often been neglected in academic and policy discussions. By capturing the unique drivers and barriers to cryptocurrency adoption in Baluchistan, the study offers valuable insights for theory development and digital financial inclusion strategies in similar high-risk and underserved contexts.

METHODS

This study adopted a quantitative research approach to investigate the key factors influencing cryptocurrency acceptance in Iran's Baluchistan region. The research design was structured in two stages. First, an exploratory factor analysis (EFA) was conducted to identify the underlying dimensions associated with cryptocurrency adoption. A structured questionnaire comprising 20 items was developed based on a comprehensive literature review and consultations with domain experts in cryptocurrency and behavioral finance. Responses were collected using a 5-point Likert scale from 200 participants actively engaged in cryptocurrency trading in Baluchistan. In the second stage, multiple linear regression analysis was performed to assess the predictive power of the six factors identified through EFA.

Exploratory factor analysis was selected due to its suitability for uncovering latent factors without relying on pre-existing theoretical frameworks, aligning with the study's exploratory nature. Unlike conventional deductive approaches that test established models, a deductive-inductive method was employed to identify novel factors influencing cryptocurrency acceptance. Variables were initially selected through an extensive review of domestic and international literature on technology adoption and cryptocurrency use. These variables were then refined through iterative consultations with experts, who evaluated their relevance and clarity. The finalized variables, summarized in Table 1, formed the basis for a 20-item questionnaire designed to capture the behavioral, economic, and social dimensions of cryptocurrency adoption.

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The target population consisted of individuals actively participating in cryptocurrency trading in Baluchistan, Iran, including those who are involved in buying, selling, or holding digital currencies. A simple random sampling method was employed to ensure representativeness within this population. Participants were recruited through online cryptocurrency trading platforms, local digital finance communities, and social media groups focused on cryptocurrency in Baluchistan. To enhance accessibility, the questionnaire was distributed in both digital and paper-based formats, accommodating the region's varying levels of technological infrastructure. A total of 200 respondents completed the survey, satisfying the recommended sample size for EFA, which requires 5–10 observations per variable (20 variables × 10 = 200). This sample size ensures statistical robustness while accounting for the region's logistical constraints, such as limited internet access and geographic dispersion.

Table. 1 Main Variables of the Study

Row	Questions
1	There is no need for high capital to enter this market
2	Earning income
3	Low financial ability of people to enter other markets (constructions, gold, dollar, …)
4	Low return of production activities in the country
5	Fluctuations and the absence of economic stability in the country
6	Inflation expectations and try to maintain the value of our assets
7	The failure of the Iranian stock market
8	High fluctuations in the value of the national currency and the need for income in dollars
9	The significant influence of social networks
10	I entered this market due to the profit made by friends and relatives
11	I entered this market due to the suggestion of my friends
12	I entered this market because of my risk-taking spirit
13	I entered this market due to the impossibility of tracking my capital and keeping my assets hidden
14	Entering this market does not require a degree from a university or special courses
15	I entered this market due to the existence of a legal gap in the country to ban the buying and selling of cryptocurrencies
16	Not paying tax
17	I entered this market due to the absence of Sharia prohibition in buying and selling cryptocurrencies
18	My confidence in the bright future of this market
19	I have enough and reliable information about this market
20	Optimism about the acceptance of these types of assets in the near future by people and governments

The 20-item questionnaire was analyzed using SPSS software to perform EFA, which identified the underlying factors explaining the correlation patterns among the observed variables. Principal component analysis with varimax rotation was applied to extract the most significant factors. Then, the resulting factors were used in a multiple linear regression analysis to evaluate their predictive impact on cryptocurrency acceptance.

The combination of EFA and regression analysis enabled a comprehensive exploration of the behavioral, economic, and social drivers of cryptocurrency adoption in Baluchistan's unique context.

Factor analysis is used to uncover the underlying variables of a phenomenon or to summarize a set of data. The primary data utilized is the correlation matrix constructed from the analyzed variables. Unlike other statistical methods, factor analysis does not predefine dependent variables. It functions based on two main types: exploratory and confirmatory factor analysis. By creating a correlation matrix, factor analysis reveals clusters of variables. Variables within each cluster show strong correlations with one another but minimal correlations with variables in other clusters. Variables lacking correlation with any others are typically removed, as a reasonable level of correlation among analyzed variables is expected. Exploratory factor analysis, specifically using the factor validity index, assesses the construct validity of the questionnaire. It determines whether the questionnaire measures the intended indicators (Khani et al., 2020).

In this research, the questionnaire's internal consistency, or reliability, is measured using Cronbach's alpha. As internal consistency increases, the alpha coefficient also rises. This indicates that the questions or items are highly relevant to the target construct (the variable related to the research hypotheses). A value exceeding 0.7 is generally regarded as indicative of good reliability. This research's alpha coefficient of 0.846 demonstrates excellent internal consistency, signifying that the 20 questions effectively measure a latent variable.

After conducting the exploratory factor analysis (EFA) that identified key latent factors influencing cryptocurrency acceptance, multiple linear regression analysis was used to evaluate the magnitude and significance of these factors' influence on the dependent variable: Cryptocurrency Acceptance. Regression analysis directly quantifies the predictive strength of independent variables, making it especially valuable for hypothesis testing and model validation in behavioral studies.

We employed multiple linear regression to investigate how key factors, derived from exploratory factor analysis (EFA), predict cryptocurrency acceptance (CA). The model is expressed as:

$$\mathrm{CA} = \beta_0 + \beta_1\mathrm{FIN} + \beta_2\mathrm{ECN} + \beta_3\mathrm{SOC} + \beta_4\mathrm{PER} + \beta_5\mathrm{MAN} + \beta_6\mathrm{TRU} + \varepsilon$$

Where:

CA = Cryptocurrency Acceptance (dependent variable)

FIN = Income and Financial Factors

ECN = National Economic Fluctuations

SOC = Social Influence

PER = Personality

MAN = Managerial Factors

TRU = Trust

ε = Error term

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As indicated in the EFA, each factor score was calculated by averaging the Likert-scale responses of items linked to that factor. This approach ensures that the scores accurately represent the underlying constructs. The regression analysis was conducted using SPSS. Regression provides a simple method to evaluate each factor's direct contribution to cryptocurrency acceptance, aligning with our goal of identifying key drivers.

It is crucial to verify that the model's underlying statistical assumptions are met. Table 2 displays the diagnostic tests conducted to evaluate the regression model's suitability and reliability used in this study. First, the Shapiro-Wilk test was conducted to evaluate the normality of residuals. A p-value of 0.15 indicates that the residuals do not significantly deviate from a normal distribution. This supports the assumption of normality, which is essential for valid hypothesis testing and confidence interval estimation.

Table. 2 Statistical Assumption Checks for Regression Model Validity

Assumption	Test/Method	Result	Interpretation
Normality of Residuals	Shapiro-Wilk test	p = 0.15	Residuals are normally distributed, supporting model validity.
Linearity	Scatterplot of predicted vs. residuals	No curvilinear patterns observed	The linear relationship between predictors and outcome is confirmed.
Constant Variance	Breusch-Pagan test	p = 0.09	Homoscedasticity is present, indicating consistent residual variance.
No Autocorrelation	Durbin-Watson statistic	1.92 (close to 2)	Residuals are independent, with no significant autocorrelation.
No Multicollinearity	Variance Inflation Factors (VIFs)	All VIFs < 2 (see Table 10)	No excessive correlation among predictors, ensuring model stability.

Source: results of the research

We analyzed a scatterplot of predicted values against the residuals to verify linearity. The lack of clear curvilinear patterns indicates that the relationship between the independent and dependent variables is indeed linear, fulfilling the criterion for multiple linear regression. We employed the Breusch-Pagan test to assess the homogeneity of variance (homoscedasticity). The p-value obtained was 0.09, which exceeds the conventional significance threshold of 0.05. This suggests that the variance of residuals remains relatively constant across different levels of the independent variables. Therefore, this finding supports the assumption of constant error variance.

The Durbin-Watson statistic was employed to identify autocorrelation in the residuals. The resulting value of 1.89 is nearly at the ideal level of 2, indicating that the residuals are uncorrelated and meet the independence assumption. Finally, we calculated the Variance Inflation Factors (VIFs) to evaluate multicollinearity among all predictor variables. All VIF values fell below 2, suggesting a minimal correlation between the independent variables. This result indicates that multicollinearity is not an issue, allowing for stable and interpretable regression coefficients. In conclusion, all diagnostic tests validate that the assumptions needed for reliable multiple regression analysis are satisfied, which enhances confidence in the model's results and their applicability.

RESULTS AND DISCUSSION

Table 3 summarizes the demographic characteristics of the study participants. The results indicate that the largest age group among respondents completing the questionnaire was between 30 and 40 years old. Additionally, 90% of respondents identified as male, and most held a master's degree. Table 3 further reveals that most participants have less than one year of experience in the cryptocurrency market, while 34.8% possess experience between one and three years.

Prior to performing factor analysis, evaluating the data's suitability is essential. This involves assessing whether the sample size and the interrelationships among the variables are sufficient for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is designed specifically for exploratory factor analysis and signals data sufficiency. Its values range from 0 to 1: below 0.5 indicates unsuitability for factor analysis, values between 0.5 and 0.69 suggest caution, and scores above 0.7 show that current correlations in the data are appropriate for analysis.

Table. 3 The demographic characteristics of the study

Demographic Variable		Percentage
Age	Less than 20	1.5
	20-25	30.3
	30-40	47
	More than 40	21.2
Gender	Male	90
	Female	10
Education	Diploma	10.6
	College	10.6
	Bachelor	34.8
	Master degree	37.9
	PhD	6.1
Experience	Less than 1 year	56.1
	1-3	34.8
	3-5	7.6
	More than 5	1.5

Source: results of the research

Data suitability is further confirmed by Bartlett's test, where a significance level below 5% suggests rejecting the identity assumption in the correlation matrix, indicating

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that factor analysis is suitable for uncovering the underlying structure (factor model). Our study's KMO index, nearing 0.7, affirms the model's robustness and suggests that the data concerning factors influencing "acceptance of cryptocurrencies in Baluchistan" is appropriate for factor analysis. Furthermore, the significant result of Bartlett's test (Sig < 0.01) further supports the rejection of the identity assumption, validating the use of factor analysis for structure identification.

Table. 4 Bartlett's Test and Numerical Value of KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**0.697**
Bartlett's Test of Sphericity Approx. Chi-Square	358.367
df	190
Sig.	0.000

Source: results of the research

The regression model accounts for 53.6% of the variance in cryptocurrency acceptance (R^2 = 0.536), which is regarded as a considerable effect size in the behavioral and social sciences (Cohen, 1988). The F-statistic of 35.42 is significant at the 0.001 level, demonstrating that the overall regression model is a good fit. Summary of the regression model predicting cryptocurrency acceptance (N=200): The R^2 of 0.536 shows that 53.6% of the variance is explained, aligning closely with findings from Rahayu (2022) regarding cryptocurrency adoption in Indonesia (R^2 = 0.50). The Adjusted R^2 of 0.521, similar to R^2, indicates that the six predictors provide meaningful contributions without unnecessary complexity. The ANOVA results affirm the statistical significance of the model.

Table. 5 Model Summary and ANOVA

Model	R	R^2	Adjusted R^2	Std. Error	F	Sig.
Regression	0.732	0.536	0.521	0.482	35.42	<0.001

Source: results of the research

Table 6 presents the eigenvalues and variance associated with the identified factors. The "Factors/Components" column displays the initial number of factors determined in the first stage of factor analysis. Since 20 variables were included in the study, 20 initial factors were generated. The "Initial Eigenvalues" column shows the initial eigenvalues for each factor, represented as the total explained variance. This variance is further expressed as a percentage of the total variance along with a cumulative percentage.

An eigenvalue for each factor represents the proportion of the total variance of the variables explained by that specific factor. It can be calculated by summing the squares of the factor loadings for all variables within that factor. Therefore, eigenvalues indicate the exploratory importance of the factors concerning the variables. A low eigenvalue

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signifies that the factor plays a minor role in explaining the variance of the variables. The "Eigenvalues of Extraction Factors without Rotation" column presents the explained variance of factors with eigenvalues exceeding 1. Finally, the "Eigenvalues of Rotated Extracted Factors" column displays the values for extracted factors after rotation.

Kaiser's criterion was initially used to determine the number of factors to retain. This criterion states that only factors with an eigenvalue of 1 or higher are potential sources of variation within the data. In Table 5, six factors influencing cryptocurrency acceptance (factors 1 to 6) have eigenvalues greater than 1, indicating their capacity to explain variances and justifying their inclusion in the subsequent analysis. These six factors together account for 62.378% of the total variance of the variables.

Table. 6 Percentage of variance and specific values of factors affecting the acceptance of cryptocurrencies in the Baluchistan region

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	4.165	20.825	20.825	4.165	20.825	20.825	2.542	12.711	12.711
2	2.657	13.284	34.109	2.657	13.284	34.109	2.378	11.889	24.600
3	1.795	8.974	43.083	1.795	8.974	43.083	2.296	11.482	36.082
4	1.377	6.886	49.969	1.377	6.886	49.969	1.875	9.375	45.457
5	1.296	6.478	56.447	1.296	6.478	56.447	1.752	8.761	54.218
6	1.186	5.931	62.378	1.186	5.931	62.378	1.632	8.159	62.378
7	.981	4.903	67.281						
8	.919	4.597	71.878						
9	.816	4.078	75.956						
10	.754	3.768	79.724						
11	.665	3.326	83.051						
12	.602	3.012	86.063						
13	.510	2.548	88.611						
14	.503	2.514	91.125						
15	.442	2.209	93.334						
16	.345	1.723	95.057						
17	.311	1.554	96.611						
18	.283	1.415	98.026						
19	.219	1.096	99.123						
20	.175	.877	100.000						

Source: results of the research

The naming of each factor should reflect the shared meaning of the variables with significant factor loadings within that factor. This name essentially serves as a

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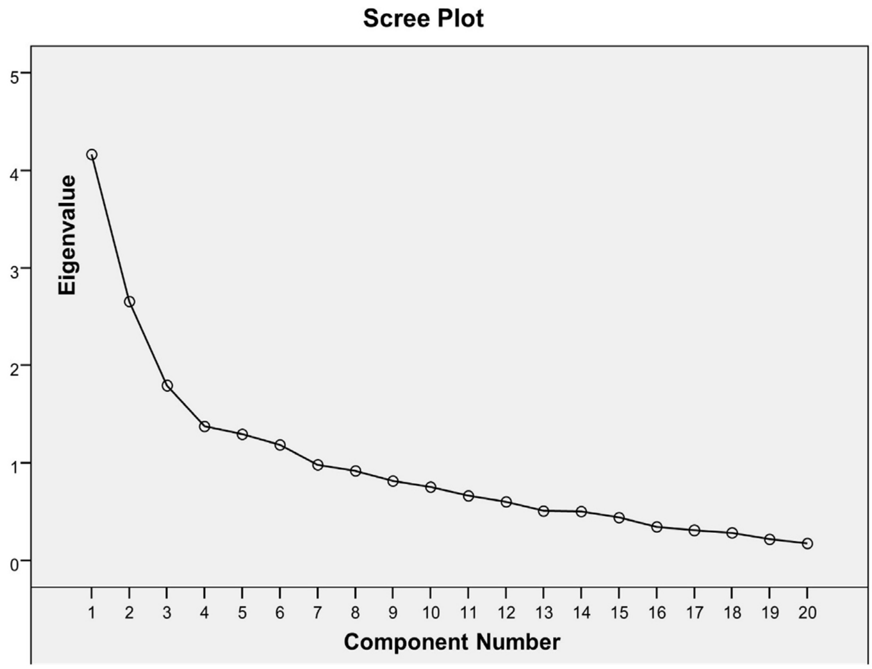
conceptual umbrella for those variables. Naturally, variables with higher factor loadings hold greater importance in the naming process and exert a more substantial influence on the selected title or label that represents the factor's underlying concept. One recommended approach for factor naming involves isolating variables with high factor loadings (above 0.6) and then naming the factor based on the common characteristics exhibited by these variables. In other words, variables with low factor loadings play a minimal role in factor naming.

A diagram of the mountain slope (rocks or pebbles) determines the number of factors. Examining the scree plot is recommended to further refine the exact number of factors to retain. This visual representation confirms the eigenvalue criterion presented in Table 6. As shown in Diagram 1, six factors have eigenvalues exceeding 1. This indicates that 20 variables can be effectively reduced to 6 factors.

Figure 1. Slope diagram of the Range of Factors



The unrotated matrix, also known as the component matrix, represents the factor analysis components before rotation and displays the correlations between the extracted variables and factors. Since this matrix does not reveal a clear pattern for identifying factors, a rotated matrix is employed to achieve a more distinct layout. Due to the complexities involved in interpreting results with diagonal rotation methods and the relative ease associated with orthogonal rotation methods, most researchers select the latter (Henson & Roberts, 2006). Orthogonal rotation can be accomplished through Varimax, Quartimax, and Equimax. Varimax is the preferred method in many software programs, including SPSS (Zabardast, 2016). Given that orthogonal rotation assumes uncorrelated factors with a correlation coefficient of zero, Pearson's correlation test was

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conducted to verify this assumption. The results presented in Table 7 demonstrate that the correlation coefficient for all factors is indeed zero, confirming their uncorrelated nature. This allows for using orthogonal methods like the Varimax rotation to rotate the factors.

Table 7. Factor Correlation Test

		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Factor 1	Pearson Correlation	1	0.000	0.000	0.000	0.000	0.000
	Sig. (2-tailed		1.000	1.000	1.000	1.000	1.000
	N						
Factor 2	Pearson Correlation	0.000	1	0.000	0.000	0.000	0.000
	Sig. (2-tailed	1.000		1.000	1.000	1.000	1.000
Factor 3	Pearson Correlation	0.000	0.000	1	0.000	0.000	0.000
	Sig. (2-tailed	1.000	1.000		1.000	1.000	1.000
Factor 4	Pearson Correlation	0.000	0.000	0.000	1	0.000	0.000
	Sig. (2-tailed	1.000	1.000	1.000		1.000	1.000
Factor 5	Pearson Correlation	0.000	0.000	0.000	0.000	1	0.000
	Sig. (2-tailed	1.000	1.000	1.000	1.000		1.000
Factor 6	Pearson Correlation	0.000	0.000	0.000	0.000	0.000	1
	Sig. (2-tailed	1.000	1.000	1.000	1.000	1.000	

Source: results of the research

Table 8 shows the rotated matrix for the effective factors or criteria of cryptocurrency acceptance. This matrix can be interpreted more easily than the previous unrotated matrix. The higher the absolute value of these coefficients, the more critical the relevant factor is in the desired variable's total changes (variance). The results show that 20 variables are summarized in 6 more general factors, and each variable's factor load is shown in the corresponding sub-factor.

The rotated factor matrix requires selecting significant factor loadings. The most common practice involves focusing on variables with factor loadings of 0.4 or higher. While some sources consider a minimum factor loading of 0.3 acceptable, factor loadings can generally be categorized as follows: 0.3 (acceptable level of significance), 0.4 (more acceptable level of significance), and 0.5 (high acceptable level of significance). Our research chose a factor loading of 0.5 as the threshold.

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Table. 8 Matrix of Rotated Factors and Their Factor Load

	Component					
	1	2	3	4	5	6
X1	0.502					
X2	0.840					
X3	0.645					
X4	0.750					
X5		0.543				
X6		0.694				
X7		0.784				
X8		0.810				
X9			0.592			
X10			0.542			
X11			0.648			
X12				0.552		
X13				0.516		
X14				0.641		
X15					0.501	
X16					0.511	
X17					0.682	
X18						0.628
X19						0.510
X20						0.522

Source: results of the research

Factor naming emphasizes aligning with the shared meaning of variables that exhibit significant factor loadings within each factor. This essentially provides a conceptual umbrella for the associated variables. Naturally, variables with higher factor loadings carry more weight in the naming process and have a more substantial influence on the chosen label that best represents the underlying concept of the factor. One practical approach involves isolating variables with high factor loadings (above 0.6) and naming the factors based on their common characteristics. In other words, variables with low factor loadings have a minimal role in the naming process.

Table 9 demonstrates consideration for theoretical and experimental texts in this field, along with adherence to naming principles and practices. The extracted factors are designated as follows: income and financial factors, national economic fluctuations, social influence, personality, managerial factors, and trust.

The 20 research items were effectively reduced to six factors through exploratory factor analysis. These six factors were identified as key ranking indicators for the participating respondents. They were named based on the items included within each factor and the shared concepts derived from those items. The table of eigenvalues shows the variance explained by each factor. According to the total cumulative variance percentage, their combined predictive power totals 62.378%. Therefore, six factors were identified as crucial for developing a ranking model for cryptocurrency acceptance: income and financial factors, national economic fluctuations, social influence, personality, managerial factors, and trust.

Table 9. Classification and Naming of Factors

Factor name	Factor Loading	Indicator
Income and financial factors	0.502	There is no need for high capital to enter this market
	0.840	Earning income
	0.645	Low financial ability of people to enter other markets
	0.750	Low return of production activities in the country
National economic fluctuations	0.543	Fluctuations and absence of economic stability in the country
	0.694	Inflation expectations and trying to maintain the value of our assets
	0.784	The failure of the Iranian stock market
	0.810	High fluctuations in the value of the national currency and the need for income in dollars
Social influence	0.592	The great influence of social networks
	0.542	I entered this market due to the profit made by friends, and relatives
	0.648	I entered this market due to the suggestion of my friends
Personality Traits	0.552	I entered this market because of my risk-taking spirit
	0.516	I entered this market due to the impossibility of tracking my capital and keeping my assets hidden
	0.641	Entering this market does not require a degree from a university or special courses
Managerial and legal factors	0.501	I entered this market due to the existence of a legal gap in the country to ban the buying and selling of cryptocurrencies
	0.511	Not paying tax
	0.682	I entered this market due to the absence of Sharia prohibition in buying and selling cryptocurrencies
Trust	0.628	My Confidence in the bright future of this market
	0.510	I have enough and reliable information about this market
	0.522	Optimism about the acceptance of these types of assets in the near future by people and governments

Source: results of the research

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Table 10 presents the regression coefficients, which include unstandardized (B) and standardized (β) coefficients, standard errors, t-statistics, p-values, VIFs, and 95% confidence intervals. This study investigated the determinants of cryptocurrency acceptance in Baluchistan, a region characterized by economic underdevelopment, political uncertainty, and social conservatism. The findings from exploratory factor analysis (EFA) and multiple regression analysis provide a multifaceted understanding of how both individual and contextual factors shape cryptocurrency adoption in this region. The results of the study offer theoretical and practical implications, mainly when situated within the frameworks of technology adoption and behavioral economics.

Table 10. Regression Coefficients

Predictor	B	SE	β	t	p-value	VIF	95% CI for B
Intercept	1.102	0.222	—	4.960	0.001	—	[0.666, 1.538]
Income & Financial	0.376	0.062	0.401	6.060	0.001	1.620	[0.254, 0.498]
National economic fluctuations	0.341	0.065	0.362	5.250	0.001	1.710	[0.213, 0.469]
Social influence	0.234	0.060	0.267	3.900	0.001	1.490	[0.116, 0.352]
Personality traits	0.146	0.053	0.163	2.760	0.006	1.350	[0.042, 0.250]
Managerial and legal factors	0.128	0.052	0.137	2.460	0.014	1.420	[0.026, 0.230]
Trust	0.108	0.050	0.121	2.160	0.032	1.380	[0.010, 0.206]

Source: results of the research

The regression analysis confirmed the statistically significant influence of six latent constructs—income and financial factors, national economic fluctuations, social influence, personality traits, managerial/legal factors, and trust—on the intention to adopt cryptocurrencies. Among these, income, financial motivations, and national economic fluctuations emerged as the most powerful predictors. These results respond to the study's initial research question: "What are the key determinants influencing the adoption of cryptocurrency in Baluchistan?". The findings reflect Baluchistan's macroeconomic environment, characterized by restricted industrial activity, elevated unemployment rates, and pervasive poverty that compel residents to explore alternative sources of income. Under these conditions, the appeal of cryptocurrency, especially its perceived ability to generate swift profits and autonomy from traditional banking, is heightened.

The dominance of income-related motivations reflects the financial desperation faced by many individuals in Baluchistan. The region suffers from chronic underinvestment and a weak manufacturing base, with most residents relying on informal sectors such as cross-border trade or subsistence agriculture. Additionally, prolonged droughts have decimated agricultural productivity, pushing more people toward alternative markets. In this context, cryptocurrencies offer a perceived escape from financial marginalization. Even individuals with limited capital appear willing to participate, viewing digital assets as tools for financial survival rather than speculative investment. These observations corroborate the earlier findings of Abu-Shanab (2013), emphasizing the central role of income as a determinant of technology adoption in constrained economic settings.

National economic instability also significantly influenced the acceptance of cryptocurrency. Iran's broader economic environment—shaped by international sanctions, currency depreciation, inflation, and fiscal mismanagement—creates a pervasive sense of uncertainty that directly impacts public behavior. The Rial's devaluation, coupled with high inflation and a loss of trust in traditional savings mechanisms, has led to an accelerated interest in alternative assets such as cryptocurrencies, gold, and foreign currencies. The 2019 collapse of the Tehran Stock Exchange, where the index plummeted after reaching a historic high, intensified this trend. Many citizens who suffered losses in that market have redirected their capital toward more autonomous and globally integrated instruments like cryptocurrencies. This result supports theories of risk-aversion and capital preservation as key motivators during economic turbulence. Research indicates that due to the instability of the domestic economy and high inflation, capital is directed toward valuable assets to preserve its value. Consequently, in Iran, a portion of people's capital has flowed into the cryptocurrency market in response to domestic economic challenges.

Social influence also demonstrated a significant effect on adoption. This result aligns with the Theory of Reasoned Action, which posits that subjective norms significantly shape individual behavioral intentions. In a tightly knit and community-oriented society like Baluchistan, individuals are highly influenced by their immediate social circles. Family opinions, peer behaviors, and religious leaders play crucial roles in legitimizing or delegitimizing certain practices. As cryptocurrencies gain traction among influential members of the community, the normalization of this technology spreads quickly. A key characteristic of the Baluchistan region is its traditional way of life. Strong family ties and a close-knit community foster awareness of each other's experiences and events. This social and cultural context facilitates the rapid spread of technological adoption and use. These results are in line with the findings of Verkasalo et al. (2010), and they underscore the need for adoption models to integrate culturally sensitive variables, especially in traditional societies.

Personality traits were another notable predictor, suggesting that intrinsic differences in risk tolerance, openness to innovation, and financial behavior play a non-negligible role in shaping acceptance. Individuals with higher levels of financial self-efficacy and a proclivity for autonomy may be more inclined to experiment with decentralized digital systems. This is especially relevant in regions where formal financial literacy programs are lacking, and people rely heavily on personal judgment and social cues. The findings are consistent with prior studies by Özbek et al. (2014) and Svendsen et al. 2013), which emphasized the role of personality in shaping technology adoption.

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Managerial and legal factors further contributed to explaining the variance in adoption behavior. In the absence of clear governmental regulations, individuals often interpret legal ambiguity as a space for opportunity rather than deterrence. The lack of taxation on cryptocurrency transactions, in conjunction with inadequate financial oversight, creates incentives for informal economic activities, including tax evasion and capital mobility. Rahayu (2022) highlights how such loopholes can contribute to the growth of underground economies. In Baluchistan, where institutional trust is already limited, the perception of regulatory gaps serves as a functional enabler of adoption. For many cryptocurrency holders in Iran, tax avoidance is a primary motivator for cryptocurrency trading. Transactions carried out using cryptocurrency as a substitute for cash are not currently subject to tax reporting due to the absence of specific regulations regarding cryptocurrency transactions.

Trust in the cryptocurrency market was also statistically significant, albeit with a smaller effect size. This reflects the dual nature of trust in high-risk environments. On one hand, technological trust facilitates participation by reducing perceived uncertainty; on the other hand, necessity-driven behavior may override cautious evaluation. Setiawan and Widanta (2021), Folkinshteyn and Lennon (2016), Dhagarra et al. (2020), Wang et al. (2015), and Chang et al. (2017) all emphasize the foundational role of trust in shaping digital engagement. In Baluchistan, trust appears to stem more from communal reinforcement and anecdotal success stories than from systematic evaluation of cryptocurrency platforms. This dynamic warrants closer examination, especially as fraudulent schemes remain a risk.

An additional layer of complexity in Baluchistan concerns religious interpretations of cryptocurrency. The region's deeply rooted Islamic traditions introduce ethical and jurisprudential hesitations about whether trading digital currencies is halal (permissible) or haram (forbidden). While this study did not measure religiosity directly, it observed that some respondents expressed concern about the Shariah-compliance of their financial decisions. Hasan et al. (2023) and Shahab et al. (2022) have debated the Islamic legitimacy of cryptocurrencies, particularly about speculation (maysir) and uncertainty (gharar). These perspectives merit deeper qualitative exploration in future studies, especially as religious endorsement or condemnation can significantly alter user behavior in Islamic communities.

Multicollinearity diagnostics confirm that the predictors are statistically independent, bolstering the credibility of the regression model. These results reveal a complex but coherent picture of cryptocurrency adoption in Baluchistan, one that integrates structural economic hardship, sociocultural norms, personal agency, regulatory ambiguity, and emerging trust in decentralized finance. By contextualizing these findings within Baluchistan's unique socio-economic and political landscape, this study not only contributes to the literature on digital finance but also offers practical insights for policymakers, financial educators, and regulatory bodies seeking to engage with marginalized populations.

These findings directly address and affirm all research questions, while also challenging the universality of mainstream technology adoption models. They highlight the necessity of developing contextually grounded frameworks to understand digital finance in marginalized and transitional settings. These results offer several insights. First, the dominance of income and economic fluctuations as predictors underscores the role of cryptocurrencies as a survival mechanism in Baluchistan, contrasting with their speculative role in developed economies. Second, the significant influence of social and personality factors highlights the interplay of cultural and individual dynamics, extending global adoption models (e.g., TAM) to a marginalized context. Third, the weaker role of trust suggests that necessity-driven adoption may bypass conventional trust-building processes, a finding with implications for policymakers aiming to regulate cryptocurrencies in unstable economies. Compared to prior studies (e.g., Xia, 2022; Shahzad et al., 2024), which emphasize universal factors like ease of use, this analysis reveals the primacy of context-specific drivers—economic hardship, community influence, and regulatory gaps—in shaping adoption in Baluchistan.

CONCLUSIONS

This study explored the key factors influencing cryptocurrency adoption in Iran's Baluchistan region through a two-step quantitative approach: exploratory factor analysis, followed by multiple regression. The findings of the study revealed that economic factors, particularly income constraints and national financial instability, are the strongest predictors of adoption. Social influence, personality traits, institutional gaps, and trust also significantly contribute to shaping individuals' decisions to engage with cryptocurrency. These results confirm that in economically marginalized areas, necessity and perceived financial insecurity play a dominant role in motivating participation in decentralized finance.

Despite its insights, the study's focus on Baluchistan limits its generalizability, and its quantitative approach may miss nuanced user perspectives that qualitative methods could reveal. Future research can compare other Iranian regions or similar developing economies and adopt longitudinal designs to track evolving trends. To leverage cryptocurrencies for financial inclusion, Iranian policymakers should enact clear regulations, license trading platforms, and develop fair tax policies to curb fraud and underground economies. Addressing religious concerns through dialogue with Islamic scholars, enhancing security in exchanges, and offering public education on blockchain technology are also critical to fostering informed adoption. These measures can transform cryptocurrency use in Iran from a necessity-driven response to a strategic tool for economic empowerment, aligning with regional needs and global blockchain advancements seen in countries like Turkey and the United Arab Emirates.

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