Financial Risk-Taking Behavior: A Quest for Determining Reliable Instruments to Measure

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Abstract

This study intends to provide a consistent and valid instrument for assessing financial risk-taking behavior by overcoming the shortcomings of current tools, including cultural bias and theoretical inadequacies. Drawing from behavioral finance and psychology theories, the study investigates how human characteristics (e.g., risk tolerance, overconfidence), economic circumstances, financial literacy, and cultural settings affect financial decision-making. The study finds four essential aspects of financial risk-taking behavior using qualitative and quantitative methods, including factor analysis and network analysis: Financial Risk-Taking, Psychological and Social Risk-Taking, Risk Aversion and Safety, and Thrill-Seeking. Data suitability for factor analysis is confirmed by the Kaiser-Meyer-Olkin (KMO) score of 0.683 and a notable Bartlett's Test of Sphericity. Initially, twelve things were tested; eleven were kept following examination. The tool shows reasonable psychometric qualities, providing a more complex view of risk-related behavior in several contexts. The network study confirms the structural links among the variables even more. By giving a culturally flexible, theoretically based, and empirically validated scale appropriate for both academic research and practical financial counseling, this work adds to behavioral finance.

Keywords: *financial risk-taking behavior, scale development, behavioral finance*

This study develops a culturally unbiased financial risk assessment tool, identifies four core dimensions of risk-taking (Financial, Psychological/Social, Risk Aversion, and Thrill-Seeking), validates findings through factor and network analysis, and provides a practical instrument for researchers and financial counselors

Background

Financial risk-taking behavior refers to the decisions that people or organizations make when faced with the possibility of financial gain or loss. Such behavior is influenced by a variety of factors, including personal psychology, economic situations, and a variety of specific circumstances. Understanding financial risk-taking is essential in fields like behavioral finance, economics, and psychology because it helps predict market behavior, design financial products, and create policies to protect investors (Kahneman & Tversky, 1979). The prospect theory of Kahneman and Tversky (1979) validates that people evaluate risks differently based on their thinking about potential losses or gains. In addition, Ricciardi and Simon (2000) discuss how behavioral finance studies the impact of psychological factors on financial decisions. This understanding helps develop better financial tools and regulations (Lo, 2005).

Personal traits play a big part in financial risk-taking. Among several traits, one crucial trait is risk tolerance, which refers to how comfortable someone is with uncertainty and risk. People more comfortable with risk tend to make riskier financial choices (Grable, 2000). Overconfidence is another essential factor—overly confident people often think they can predict market trends better than they actually can, leading them to take on more risk than they should (Barber & Odean, 2001). Additionally, loss aversion—where people prefer avoiding losses more than they value making gains—can lead to very cautious financial decisions (Kahneman & Tversky, 1979).

Economic conditions also influence financial risk-taking. Research showed that when markets are more volatile, people perceive more significant risk and may make more cautious decisions (Schwert, 1989). Likewise, interest rates play a decisive role. When interest rates are low, people might be more likely to invest in riskier assets because the returns on safer investments are less appealing (Bernanke & Kuttner, 2005).

Financial risk-taking behavior is nonetheless a luck game driven by windfall gain. Financial knowledge and education are key in shaping how people take risks, as those with a better

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understanding of financial markets are often more confident in making informed decisions (Lusardi & Mitchell, 2014). Cultural differences also affect financial behavior, as attitudes toward money and risk vary across cultures, shaping how people make financial choices (Hofstede, 2001). Finally, personal experience matters—previous success or failure in financial decisions can shape how people assess and handle risks in the future (Weber et al., 2002).

Problem statement

Assessing risk-taking behavior is crucial for understanding various psychological and behavioral outcomes. However, creating accurate and reliable tools to measure this behavior has been challenging in psychology. Many existing tools have issues like cultural biases, weak reliability, and lack of strong theoretical support. These problems show the need for better measurement instruments. This study aims to develop a more reliable and well-founded tool to assess risk-taking behavior across different groups of people. Using quantitative and qualitative methods, the new tool will provide a more complete evaluation of risk-taking, covering its various aspects. This will result in a valid instrument used in clinical settings and research, helping improve our understanding of the factors and outcomes linked to risk-taking behavior (Weber et al., 2002; Byrnes et al., 1999).

Research question

- What are the primary dimensions of financial risk-taking behavior(RTB) that build a reliable instrument to assess and measure such behavior?
- How do cultural factors influence risk-taking behaviors, and how can they be accounted for when developing a measuring behavior?

Objectives

- Treatment options should be included in their instrumentalities for measuring behavior to assess the significant dimensions of risk-taking behavior.
- To assess the impact of economic, knowledge, and cultural factors on risk-taking behaviors and to determine the development of tools for measuring behaviors.

Literature review

DeVellis' book, "Scale Development: Theory and Applications," is a key resource in creating measurement tools. It offers a detailed guide on developing and validating scales, explaining their theory, how to write good items, and how to test for reliability and validity. DeVellis highlights the need to clearly define what you want to measure and develop items systematically, giving practical examples and step-by-step instructions. This book is commonly used in social sciences and health research, helping researchers build strong and reliable measurement tools (DeVellis, 2016).

Clark and Watson's article, "Constructing Validity: Basic Issues in Objective Scale Development," discusses the key challenges in creating psychological scales. They emphasize the need for clear definitions of the measured constructs, generating a wide range of items, and thoroughly testing for reliability and validity. Their work provides a solid framework to ensure that scales genuinely measure what they should, making it an essential resource in psychometrics. This article is crucial for researchers who want to develop valid and reliable psychological tools (Clark & Watson, 1995).

In their article "Scale Development Research: A Content Analysis and Recommendations for Best Practices," Worthington and Whittaker analyze scale development practices and propose guidelines to enhance the rigor and quality of these studies. They identify common pitfalls and recommend best practices for each stage of scale development, from item generation to psychometric evaluation. Their work is instrumental for researchers seeking

There is a need for better measurement instruments.

DeVellis (2016) provides a systematic guide for constructing valid scales, emphasizing clear construct definition, item generation, and rigorous psychometric testing. Clark & Watson (1995) further stress the importance of validity and reliability in psychological measurement tools. Worthington & Whittaker (2006) analyze common pitfalls in scale development and offer evidence-based recommendations to enhance methodological rigor, from item design to validation

to develop robust measurement tools in counseling psychology and related fields (Worthington & Whittaker, 2006).

The KMO Test measures how well the variables are correlated, helping to determine if factor analysis is appropriate.. In this case, sample adequacy is adequate woth 0.683, and p<0.05

Methodology

Kaiser-meyer-olkin (KMO

The **Kaiser-Meyer-Olkin (KMO) Test** and **Bartlett's Test of Sphericity** are tools used to check if data is suitable for factor analysis. The KMO Test measures how well the variables are correlated, helping to determine if factor analysis is appropriate. Its value ranges from 0 to 1, with higher values indicating that the data is suitable for factor analysis. Bartlett's Test of Sphericity checks if the correlation matrix **significantly differs** from an identity matrix, where no variables are related. If Bartlett's test is significant ($p < 0.05$), it suggests that factor analysis can be used (Kaiser, 1974).

Table 1 KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.683
Bartlett's Test of Sphericity	Approx. Chi-Square	339.322
	Df	66
	Sig.	.000

12 variables can be grouped into 4 factors, as significant attributes can be accumulated by 4 factors

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity are used to evaluate your data's suitability for factor analysis.

Total variance explained

Rotated components matrix guides the variables to keep in a particular group of factors

The Total Variance Explained table in SPSS shows how much of the overall variance in your data is accounted for by each factor or component in factor analysis. It includes eigenvalues, which tell you how much variance each factor explains. The table also shows the percentage of variance for each factor and the cumulative total. This helps researchers decide how many factors to keep based on how much of the total variance they explain. For example, if the first few factors explain most of the variance, those are typically retained for further analysis (Field, 2013).

Rotated component matrix

The Rotated Component Matrix in SPSS is a table that shows the loadings of variables on the factors after rotation in factor analysis. Rotation is done to make the factors easier to interpret by ensuring that each variable loads strongly on one factor and weakly on others. The matrix displays how much each variable is associated with the extracted factors. In this matrix, each row represents a variable, and each column represents a factor. Higher values in the matrix indicate a stronger relationship between the variable and the factor, making **understanding each factor's meaning easier**. Typically, a Varimax rotation is used for orthogonal (uncorrelated) factors, while an Oblimin rotation is used for correlated factors (Field, 2013; Pallant, 2020).

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy: 0.683. The KMO measure evaluates the proportion of variance among the variables that might be common variance. It ranges from 0 to 1, with higher values indicating **appropriate factor analysis**.

Findings

Bartlett's Test of Sphericity

Chi-Square (339.322) with df (66): A high Chi-Square value relative to the degrees of freedom indicates that the null hypothesis can be rejected.

Significance (0.000): A p-value less than 0.05 indicates that the correlation matrix is not an identity matrix. This suggests significant correlations among the variables, making the data suitable for factor analysis.

Table 1 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	3.418	28.486	28.486	3.418	28.486	28.486	2.418	20.148	20.148
2	1.854	15.447	43.934	1.854	15.447	43.934	2.046	17.047	37.195
3	1.603	13.357	57.291	1.603	13.357	57.291	1.945	16.206	53.401
4	1.166	9.720	67.010	1.166	9.720	67.010	1.633	13.609	67.010
5	.857	7.138	74.148						
6	.719	5.991	80.139						
7	.597	4.977	85.116						
8	.465	3.876	88.992						
9	.437	3.642	92.634						
10	.340	2.836	95.470						
11	.279	2.325	97.795						
12	.265	2.205	100.000						
Extraction Method: Principal Component Analysis.									

Table 2 Rotated component matrix

	Component			
	1	2	3	4
I can handle the uncertainty that the stock market entails.	.773			
I like to invest in the share market rather than a fixed deposit.	.724			
I consider myself as a risk-taker	.722			
Even though it means accepting a high degree of risk, a high return on my investment is essential.	.696			
I like the feeling that comes with taking psychological or social risks.		.872		
I like the feeling that comes from entering a new situation.		.699		
I often think about doing activities that involve physical risk.		.697		
I like the feeling that comes with taking physical risks.			-.790	
When it comes to investing, the safety of the principal is more important than returns.			.720	
I invest money, and a safe return is essential for me.			.707	
Being afraid of doing something new often makes it more fun.				.896
The greater the risk, the more fun the activity will be.				.670

Based on the rotated component matrix, out of the 12 items, it is divided into four groups. Group one consists of four items, group 2 consists of three items, group three consists of three items, and group four consists of 2 items.

The first group indicates "Financial Risk-Taking" because all the items are related to financial risk. So, it is labeled as a financial risk.

This factor could be labeled **"Psychological and Social Risk-Taking"** as it reflects a preference for psychological, social, and physical risk-taking behavior in new situations.

This factor could be labeled as **"Risk Aversion and Safety"** since it focuses on the preference for safety and aversion to physical risks, particularly in investments. However, the negative loading on "I like the feeling that comes with taking the physical risk" is eliminated.

This factor could be labeled as **"Thrill-Seeking"** because it captures the idea of enjoying risk and finding excitement or fun in risky activities, especially when fear is involved.

So, financial risk-taking behavior is categorized as follows.

Table 3 Naming new variables for the transformed variable

Financial Risk Taking	Psychological and Social Risk-Taking	Risk Aversion and Safety	Thrill-Seeking
I can handle the uncertainty that the stock market entails.	I like the feeling that comes with taking psychological or social risks.	When it comes to investing, the safety of the principal is more important than returns.	Being afraid of doing something new often makes it more fun.
I like to invest in the share market rather than a fixed deposit.	I like the feeling that comes from entering a new situation.	I invest money, and a safe return is essential for me.	The greater the risk, the more fun the activity will be.
I consider myself as a risk taker.	I often think about doing activities that involve physical risk.		
Even though it means accepting a high degree of risk, a high return on my investment is essential.			

Network analysis

Summary of network

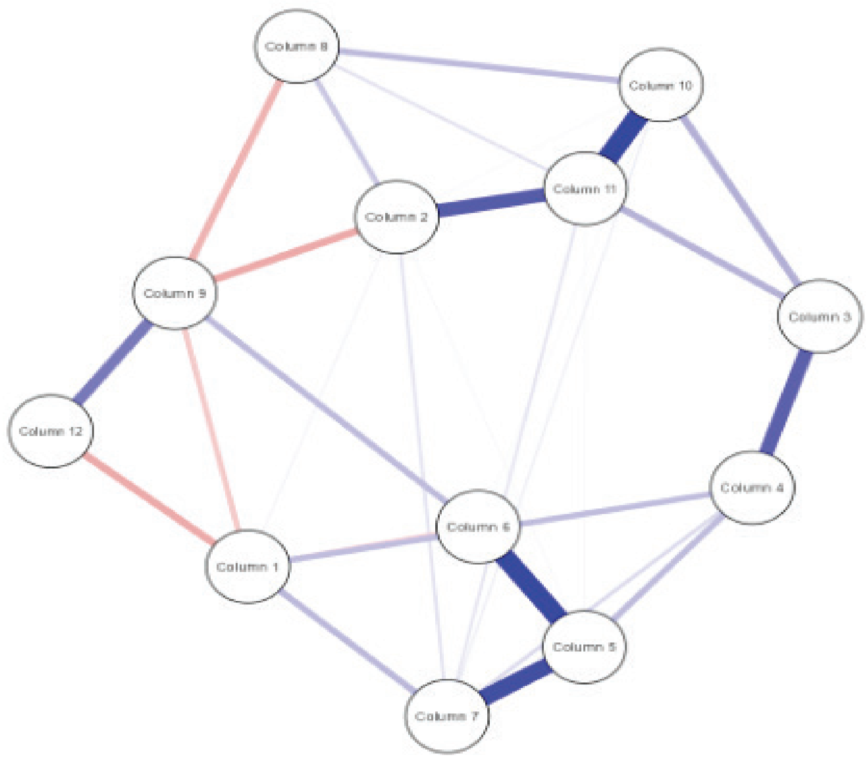

Fig: Network digram

Centrality measures per variable				
	Network			
Variable	Betweenness	Closeness	Strength	Expected influence
Q1	-0.408	-0.303	-0.296	-1.461
Q 2	0.260	0.716	0.004	-0.265
Q3	0.705	0.454	-0.544	0.329
Q 4	0.928	0.660	-0.392	0.402
Q5	0.483	0.098	1.483	1.302
Q 6	0.037	0.307	-0.160	-0.003
Q7	-1.077	-1.564	0.128	0.652
Q8	-1.299	-1.505	-1.397	-0.856
Q 9	2.042	2.095	0.486	-1.353
Q10	-0.631	-0.645	0.471	0.816
Q11	0.260	0.045	1.810	1.459
Q12	-1.299	-0.359	-1.593	-1.022

In this case, there are 12 nodes, meaning 12 distinct elements in this network represent the connections between nodes. A non-zero edge indicates a meaningful relationship between two nodes (as opposed to no connection or a zero-valued edge).

The possible number of edges in a fully connected undirected network can be calculated using the formula for combinations. Of these 66 possible edges, 29 are non-zero, meaning 29 connections exist between the nodes, representing meaningful relationships.

Q1: All centrality measures (betweenness, closeness, strength, expected influence) are negative. This suggests that Q1 has a weak position in the network, with limited influence and fewer interactions with other variables. It is not a central or connecting node.

Q2: has high closeness (0.716), meaning it is relatively close to other variables and can interact with them efficiently. However, its strength (0.004) and expected influence (-0.265) are low, indicating that its influence or impact is minimal while it is well-positioned.

Q3: shows a moderate betweenness (0.705) and closeness (0.454), suggesting it plays a connecting role and is somewhat close to other variables. However, its negative strength

(-0.544) means its connections are not strong, and the overall expected influence (0.329) is low.

Q4: has high betweenness (0.928) and closeness (0.660), indicating that it plays a significant role in connecting different parts of the network and is well-positioned. However, its strength is negative (-0.392), meaning the strength of its connections is weak. Its positive expected influence (0.402) suggests some degree of impact on the network.

Q5: has very high strength (1.483) and expected influence (1.302), meaning it has strong connections and a significant impact on the network. However, its betweenness (0.483) and closeness (0.098) are relatively low, indicating it is not a key connector but has a substantial direct influence.

Q6 shows low-to-moderate values in all measures, with the highest being closeness (0.307). It has weak connections and minimal influence overall.

Q7: has negative betweenness (-1.077) and closeness (-1.564), indicating a weak and distant position in the network. However, its strength (0.128) and expected influence (0.652) are positive, meaning that despite its isolated position, it has some direct influence.

Q8: All values for Q8 are negative, including betweenness (-1.299), closeness (-1.505), strength (-1.397), and expected influence (-0.856). This suggests that Q8 is very isolated, with minimal connection and influence in the network.

Q9: has the highest betweenness (2.042), closeness (2.095), and moderate strength (0.486). This makes Q9 a central and highly connected variable within the network, playing a key role in connecting others. However, its expected influence (-1.353) is negative, suggesting that its overall impact on the network may not be beneficial or significant despite its centrality.

Q10: has low betweenness (-0.631) and closeness (-0.645), suggesting it is not central or well-connected. However, its strength (0.471) and expected influence (0.816) are positive, indicating it still has some influence through direct connections.

Network analysis showed the relation of 12 questions among each other: in this case the analysis showed Q9 is the most central (high betweenness/ closeness) but has negative influence. Q5 & Q11 exert strong direct influence (high strength/expected influence) but aren't key connectors. Q4 bridges the network nicely but has weak connection strength. Q1, Q8, and Q12 are isolated with minimal impact. Q7 & Q10 are peripheral but retain some direct influence

Q11: has high strength (1.810) and expected influence (1.459), meaning it has strong direct connections and a significant impact on the network. However, its betweenness (0.260) and closeness (0.045) are low, indicating it is not a key connector but has a direct influence.

Q12: shows negative values for all measures, including betweenness (-1.299), closeness (-0.359), strength (-1.593), and expected influence (-1.022). Like Q8, Q12 is highly isolated, with minimal connection and influence in the network.

Conclusion

The study developed a reliable, culturally adaptable risk-taking assessment tool with validated psychometric properties (KMO=0.683), identifying three key dimensions and retaining 11 items through iterative refinement, supported by network analysis

The study successfully developed a reliable and valid tool for measuring risk-taking behavior, incorporating qualitative insights and quantitative validation. The tool's psychometric properties were assessed, showing adequate reliability and validity. The KMO measure of sampling adequacy was 0.683, indicating a mediocre but acceptable level of sampling adequacy. Bartlett's Test of Sphericity confirmed significant correlations among variables, further validating the tool's structure.

The three primary dimensions identified through EFA provide a robust framework for assessing risk-taking behavior. The study highlights the importance of considering cultural factors in tool development, ensuring the instrument is relevant across diverse contexts. The iterative process of refinement and validation underscores the necessity of ongoing evaluation to enhance the tool's effectiveness. In this study, network analysis is also done and analyzed. After the analysis, four groups were formed, and 11 items were retained out of the 12 items.

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