International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Antecedents of TQM Practices in the Banking Industry: with Specific Reference to Bangalore

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ABSTRACT

This research analyses the factors which affect Total Quality Management (TQM) practice implementation throughout Indian banks specifically evaluating institutions in Bangalore. Digital transformation combined with escalating customer demands requires businesses to grasp what enables effective implementation of TQM systems. The analysis of 211 banking professional survey data measures how strongly four variables (V4, V8, V12, V16) predict the results of TQM (V20). The analysis shows variable agreement levels amounting to moderate rates which was further supported by the significant positive correlations especially between V4 and V20. The two meaningful predictors V4 and V8 from multiple regression analysis explained 45.7% of the variance in V20 while bootstrap resampling supported these findings. The investigation reveals that bank TQM success heavily depends on leader commitment (V4) and employee involvement (V8). The low correlation strength between V20 and V12 or V16 showed these variables did not produce significant findings thus indicating contextual or interaction-related constraints. The study identifies theoretical value through TQM framework refinement as well as practical guidance that pushes banks toward enhancing leader involvement and staff involvement. The examination of TQM implementation in banking requires future studies to use longitudinal analysis techniques while expanding research boundaries to various locations for increased generalization potential and improved causal analysis

Keywords: Antecedents, Total Quality Management, Banking Industry, efficiency

Introduction

Profit and loss operations in the banking sector transformed radically throughout recent decades when traditional products shifted to customer-centric service delivery powered by technology. Total Quality Management (TQM) functions as a vital strategy for organizations today to achieve excellent performance and customer retention along with long-term competitive success because of the changing business environment (Oakland 2014; Talib et al. 2011). The manufacturing-sector-created TQM concept now works efficiently in service industries which include healthcare facilities along with education facilities and financial service companies. TQM functions through complete organizational dedication to quality execution which includes leadership and continuous improvements alongside employee participation and customer-driven strategies (Deming, 1986; Juran & Godfrey, 1999). The banking sector sees TQM as a mechanism for boosting operational efficiency and improving service quality while decreasing errors which might create unhappy customers. Quality management implementation has taken on greater importance because of digital banking development and strengthened regulatory standards and heightened customer expectations (Suresh Chandar et al., 2001). Various barriers hinder the successful implementation and variable adoption rates of TQM in institutions regardless of their regional cultures. A strategic problem exists within Indian banking because banks lack a unified quality culture throughout the industry at an operational level. Talib & Rahman (2010) showed that numerous banks embark on individual quality certification programs or acquire ISO 9001 compliance yet fail to establish continuous improvement throughout their fundamental business framework. Such short-term benefits do not lead to lasting modifications in institutional practices. Lack of empirical evidence regarding factors that promote or resist TQM adoption in banks prevents management from developing enduring quality management systems. Banks require a comprehensive understanding of TQM antecedents that involve essential internal and external contributors because this knowledge enables better execution from planning stages. Several key factors which determine whether banks adopt Total Quality Management as a philosophy or tool set include top management commitment and organizational culture together with employee involvement and customer orientation alongside technological readiness and competitive pressure as well as regulatory influence (Yusof & Aspinwall, 2000; Brah, Tee, & Rao, 2002). The factors determine the bank's approach to adopt TQM by either adopting it as an essential philosophy or applying it as a collection of tools. Bangalore, stands at the crossroads of financial and technological innovation. The worldwide start-up and IT community identifies Bangalore as a central banking hub where both national public banks interact with international private entities. The employees within the banking sector of the city demonstrate both digital competency and rising service demand patterns alongside a service-minded approach. Study of TQM implementation development factors shows excellent potential in the urban banking sector. The unique market environment in Bangalore enables researchers to directly study the development and implementation of TQM practices within Indian banks because of its strong financial institutions and customer variety and progressive mind-set. The findings obtained from this specific case enable researchers to develop quality strategies that can be applied across metropolitan banking sectors within the nation. The investigation offers researchers an irreplaceable chance to understand what makes banks adopt TQM frameworks along with their motivating elements. The research investigates what drives banks to select TQM frameworks as well as their implementation conditions because most TQM studies focus on results instead. These findings provide assistance for three player groups consisting of banks aiming for betterment, regulatory bodies interested in quality enhancement and academic researchers contributing to service quality and operations management literature (Zairi, 1994). The research could identify fresh patterns and combinations of elements which influence TQM implementation specifically the relationship between digital transformation and quality management culture that standard quality models fail to capture. The research results will provide valuable information to multiple cricholders because they will help various groups achieve TQM-goal alignment along with service quality improvement and process efficiency reduction in banking institutions. Research data should be used to create banking operation frameworks and quality standards along with performance incentives that minimize process inefficiencies within banking institutions. The study provides theoretical foundation to the advancing research on TQM applications for services operations within developing countries which aims to reduce process inefficiencies in banking institutions. The understanding of human-centric quality dimensions helps banking institutions improve employee morale while boosting performance and workplace environment along with lower process inefficiencies. Dependent users who receive improved banking services that are better designed and more responsive and reliable help decrease inefficiencies throughout banking institutions.

This study will pursue the following specific objectives:

1. To identify and analyse the key antecedents influencing the adoption of TQM practices in the banking industry.

2. To provide recommendations that support the strategic implementation and institutionalization of TQM in the Indian banking context.

3. To determine how knowledge sharing and change readiness can enhance customer focus and ease the process of automation.

Literature Review

The first study by Haralayya (2021) traces the evolution of Indian banking, highlighting milestones like nationalization and technological advancements such as UPI. It categorizes banking services and underlines their critical contribution to economic growth through innovations like mobile and online banking. Another study by Rawashdeh (2014) explores TQM practices in Jordanian banks, showing their positive effects on performance and competitive advantage, especially through strategic planning, customer focus, and process management. Pattanayak and Maddulety ([Year]) review the link between TQM and customer satisfaction in Indian banks, stressing dimensions like top management commitment and employee empowerment, while identifying challenges such as poor leadership and cultural resistance. Salah's (2018) research investigates TQM's impact on Kenyan banks, concluding that practices like employee involvement and continuous improvement enhance operational and financial outcomes. Pattanayak and Punyatoya (2015) identify eight critical TQM factors in Indian retail banking, emphasizing leadership and technological services as drivers of customer satisfaction. Another key study by Koomson (2024) highlights how TQM mediates the relationship between innovation behavior and innovation performance in Ghana's banks, with external factors playing a significant moderating role. Additional studies focus on areas such as interest rate changes on Indian bank profitability (Murty & Chowdary, 2018) and the efficiency of Jordanian banks through TQM practices (Mashal & Ahmed, 2015). Together, these studies illustrate how TQM and banking service innovation transform organizational performance across different regions. The Indian banking sector has been extensively studied across multiple dimensions, including service evolution, monetary policy transmission, cooperative banking, liquidity management, multinational bank strategies, and performance comparisons between public and private banks. Haralayya (2021) highlights the transformation of banking services through digital innovations like UPI and mobile banking, emphasizing their role in financial inclusion. Das, Mishra, and Prabhala (2015) analyse monetary policy transmission, revealing that branch-level factors— such as deposit richness and asset quality—determine lending responsiveness to CRR changes, with public banks lagging in adaptability. Gupta and Jain (2012) focus on cooperative banks, noting their challenges in resource mobilization and recovery rates, while advocating for modernization to improve efficiency. Bhati, De Zoysa, and Jitaree (2019) examine liquidity determinants, finding asset-based liquidity more critical than regulatory ratios like SLR and CRR. Caussat, Prime, and Wilken (2019) explore how French multinational banks gain legitimacy in India through strategies like isomorphism and political activism, balancing global and local demands. Performance comparisons reveal private banks outperform public banks in profitability (Goel & Rekhi, 2013), with higher ROA and NIM, while public banks struggle with credit-deposit efficiency. Karri, Meghani, and Mishra (2015) use the CAMEL model to show Bank of Baroda's slight edge over Punjab National Bank in liquidity and management. Thiagarajan and Ramachandran (2011) identify rising credit risks in public banks post-2007, linking NPAs to macroeconomic factors like inflation and export-import ratios. Collectively, these studies underscore the need for regulatory reforms, technological adoption, and governance improvements to enhance stability and competitiveness in India's banking sector.

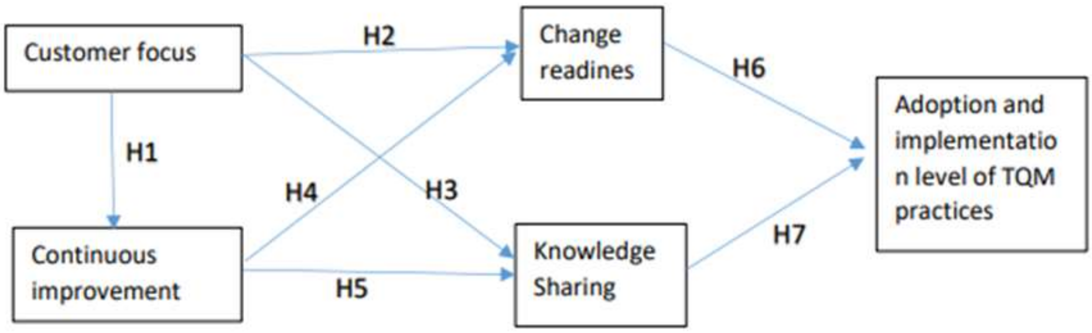

Figure 1 : Proposed conceptual model; source the authors

H1: Customer Focus has a positive impact on continuous improvement of logistics.

H2: Customer focus significantly influences change readiness in the organization.

H3: Customer focus positively influences knowledge sharing about logistics practices.

H4: Continuous improvement has a positive impact on change readiness

H5: Change readiness positively influences adoption and implementation practices of TQM

H6: Knowledge sharing positively mediates between continuous improvement and adoption and implementation practices of TQM.

Research Methodology

Research Design

The study requires quantitative analysis to measure and statistically analyse the interrelationships between leadership practices employee involvement and Total Quality Management adoption. Such research design enables scientists to objectively evaluate many different participants in order to generalize study findings (Creswell, 2014). The statistical program SPSS enables researchers to conduct thorough analysis through correlation tests and regression models alongside reliability assessment to construct validated theoretical structures and draw precise scientific findings (Pallant 2020). The research approach delivers precise results and provides standardized statistical modelling because it helps identify critical TQM predictors within the banking industry.Primary data collected through questionnaires is relevant for a sample size of 188, as it allows for standardized data collection, ensuring consistency and comparability across responses (Saunders et al., 2019). This method is efficient for gathering quantifiable insights from a moderately sized sample, enhancing the reliability of statistical analysis (Creswell, 2014).

Sample size

Research using SPSS requires 211 participants as an acceptable sample size for analysing models that contain several constructs and their indicators. The minimum sample size should equal ten times the largest number of paths that go to any latent construct in the model based on the "10-times rule" according to Hair et al. (2021). A research sample with 200 or more participants demonstrates sufficient statistical power according to Cohen (1988) because it enables detection of medium effect sizes at a 5% significance level. The data sample of 211 participants demonstrates sufficient strength for dependable and generalized outcomes when evaluated from SPSS.

Data collection:

Primary data collection stands as the most fitting approach for this research because it enables the researcher to obtain precise quantifiable findings about respondent NPS scores and digital awareness together with brand trust measurements. The standardization enabled by questionnaires results in reliable data retrieval from extensive respondent groups which facilitates analysis (Creswell & Creswell, 2018). Data collection through Likert-scale items permits researchers to measure abstract notions such as customer satisfaction along with digital confidence characteristics. When researchers gather primary data they achieve better validity because their datasets capture contemporary behavioural patterns that match the research environment unlike secondary data does.

Data Analysis

Descriptive Statistics

Table 1: Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
V4	211	1	5	3.2	0.962
V8	211	1	5	3.23	0.881
V12	211	1	5	3.2	0.866
V16	211	1	5	3.36	0.836
V20	211	1	5	3.36335	0.904805
Valid N (list wise)	211				

The score averages of variables V4 and V12 reached 3.20 and all variables showed standard deviations between .836 (V16) and .962 (V4) while V16 and V4 had the lowest and highest standard deviation respectively. The V20 variable held a 3.36 mean rating along with .90 standard deviation. The variables included in the analysis spanned from 1 to 5 in all cases. The sample data (N = 211) showed V4 and V12 achieved an average score of 3.20 with standard deviations at .96 and .87 while V8 reached 3.23 with a standard deviation of .88 (V16 averaged 3.36 with .84 and V20 reached 3.36 with .91 and V12 averaged 3.20 with .87).

Correlations:

Table 2: Correlations

Correlations						
		V4	V8	V16	V20	V12
V4	Pearson Correlation	1	.501**	.582**	.609**	.591**
V8	Pearson Correlation	.501**	1	.468**	.549**	.539**
V16	Pearson Correlation	.582**	.468**	1	.474**	.478**
V20	Pearson Correlation	.609**	.549**	.474**	1	.454**
V1 2	Pearson Correlation	.591**	.539**	.478**	.454**	1
**. Correlation is significant at the 0.01 level (2-tailed).						

Results from Pearson correlation analysis demonstrated positive statistical connections at a p level below .01 between V20 values and V4 (r = .609), V8 (r = .549), V16 (r = .474) and V12 (r = .454). The predictor variables showed positive correlation effects that reached significance.

Bootstrap

Table 3: Bootstrap

Bootstrap Specifications	
Sampling Method	Simple
Number of Samples	1000
Confidence Interval Level	95.00%
Confidence Interval Type	Percentile

The study used 1000 bootstrap samples from a simple sampling approach for bootstrap resampling. A 95% level of confidence intervals for coefficient estimates was determined using percentile methods for bootstrap resampling. The method establishes reliable measurements of coefficient uncertainty through its approach

Regression

Table 4: Regression

Descriptive Statistics						
		Statisti c	Bootstrap[a]			
			Bias	Std. Error	95% Confidence Interval	
					Lower	Upper
V2 0	Mean	3.3633 49	-.001850	.060731	3.233847	3.481752
	Std. Deviation	.90480 47	-.0045262	.0449796	.8109919	.9904701
	Mean	3.36	.00	.06	3.25	3.47
V1 6	Std. Deviati on	.836	-.003	.039	.758	.915
V8	Mean	3.23	.00	.06	3.11	3.34
	Std. Deviati on	.881	-.002	.041	.802	.962
V4	Mean	3.20	.00	.06	3.08	3.33
	Std. Deviati on	.962	-.004	.040	.877	1.036
V1 2	Mean	3.20	.00	.06	3.08	3.32
	Std. Deviati on	.866	-.003	.038	.786	.939
a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples						

The data analysis revealed that V20 had mean rate of 3.36 with standard deviation of .90 while V16 possessed equivalent mean of 3.36 but a standard deviation of .84. V8 demonstrated a mean result of 3.23 supported by standard deviation level of .88. V4 displayed a mean average of 3.20 while its standard deviation was .96. Similarly, V12 showed a mean score of 3.20 with a standard deviation value of .87. Bootstrapping methods generated mean and standard error values with low measured errors while producing dependable 95% confidence intervals for population mean estimations. The regression included V12 and V16 and V8 and V4 as predictor variables which were analysed through the enter method.V20 was the dependent variable. The regression analysis retained all the specified predictors for V20 as part of the assessment to determine their impact.

Model Summary

Table 5: Model Summary

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error	Change Statistics				
				of the Estimate	R Square Change	F Change	f1	df2	Sig. F Change
1	.676[a]	.457	.446	.6732851	.457	43.314	4	206	.000

The multivariate regression model achieved statistical significance with $F(4, 206) = 43.31$, p

$< .001$ and showed an effect size of $R^2 = .457$. This indicates V12, V16, V8 and V4 contributed to 45.7% of the variation in V20. The adjusted R^2 value reached .446 while the standard error of prediction amounted to 0.673.

ANOVA

Table 6: ANOVA

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	78.539	4	19.635	43.314	.000b
	Residual	93.382	206	.453		
	Total	171.921	210			

The analysis of variance reveals that V12, V16, V8, V4 effectively forecast V20 since $F(4, 206) = 43.314$ with a p value less than .001. These predictor variables share a substantial amount of explanatory power regarding V20.

Variables Entered/Removed			
Model	Variables Entered	Variables Removed	Method
1	V12, V16, V8, V4[b]		Enter
a. Dependent Variable: V20			
b. All requested variables entered.			

Bootstrap for Coefficients							
Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	0.784	0.012	0.209	0.002	0.414	1.216
	V16	0.107	-0.006	0.076	0.161	-0.049	0.254

.

The research proves through bootstrapped coefficients analysis that V8 ($B = .305$, $p < .001$, 95% CI [.174, .451]) and V4 ($B = .372$, $p < .001$, 95% CI [.213, .539]) substantially predict the dependent variable. The procedure confirmed that V16 ($B = .107$, $p = .161$, 95% CI [-.049,

.254]) along with V12 ($B = .013$, $p = .895$, 95% CI [-.190, .193]) did not act as significant predictors of the dependent variable.

A total of 1000 bootstrap samples were generated through simple sampling to perform the analysis. The 95% confidence intervals for coefficients received estimation through percentile methods. The method delivers dependable estimates regarding parameter uncertainty levels.

Correlations						
		V4	V8	V16	V20	V12
V4	Pearson Correlation	1	.501**	.582**	.609**	.591**
V8	Pearson Correlation	.501**	1	.468**	.549**	.539**
V16	Pearson Correlation	.582**	.468**	1	.474**	.478**
V20	Pearson Correlation	.609**	.549**	.474**	1	.454**

V12	Pearson Correlation	.591**	.539**	.478**	.454**	1
**. Correlation is significant at the 0.01 level (2-tailed).						

A significant positive correlation measuring p < .01, two-tailed existed between the variables V20 and V4 (r = .609), V8 (r = .549), V16 (r = .474) and V12 (r = .454). The relationships between predictor factors showed both moderate and strong instances of positive correlation.

Nonparametric Correlations

Case Processing Summary			
		N	%
Cases	Valid	211	100
	Excluded	0	0
	Total	211	100

Every one of the 211 cases included in the study underwent full evaluation before participating in the analysis (100.0% Case Processing Summary). No cases were omitted from the procedure because list wise deletion of variables led to total data completion. The analysis determines its results by using the entire population of samples.

Reliability Statistics

Reliability Statistics	
Cronbach's Alpha	N of Items
.908	20

The scale's reliability was established at an excellent level through its Cronbach's alpha coefficient result of .908. The measurement scale shows internal consistency due to items operating coherently to measure one construct as reliability stands at .908.

Regression

		Statistic	Bootstrap			
			Bias	Std. Error	95% Confidence Interval	
					Lower	Upper
V20	Mean	3.363349	-0.004378	0.061013	3.233847	3.477053
	Std. Deviation	0.9048047	-0.0038084	0.0456665	0.814121	0.9864711
V16	Mean	3.36	0	0.06	3.25	3.48
	Std. Deviation	0.836	-0.003	0.039	0.758	0.909
V8	Mean	3.23	0	0.06	3.11	3.35
	Std. Deviation	0.881	-0.003	0.042	0.794	0.958
V4	Mean	3.2	0	0.07	3.07	3.33
	Std. Deviation	0.962	-0.004	0.041	0.877	1.04
V12	Mean	3.2	0	0.06	3.08	3.31
	Std. Deviation	0.866	-0.003	0.038	0.788	0.937

The statistics show that participants scored V20 at M = 3.36 with SD = .90 whereas V16 and V8 received M = 3.36 and SD = .84 and SD = .88 respectively. V4 scored M = 3.20 with SD =.96 and V12 scored M = 3.20 with SD = .87. Bootstrapped means together with standard errors proved to show minimal bias when measuring population parameters while 95% confidence intervals establish a range for these parameters.

Variables Entered/Removeda			
Model	Variables Entered	Variables Removed	Method
1	V12, V16, V8, V4[b]	.	Enter
a. Dependent Variable: V20			
b. All requested variables entered.			

The regression model entered the predictor variables V12, V16, V8 and V4 simultaneously using the Enter method according to the information in the Variables Entered/Removed table. There were no variables eliminated during this procedure according to the table.

ANOVA a						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	78.539	4	19.635	43.314	.000[b]
	Residual	93.382	206	0.453		
	Total	171.921	210			

ANOVA analysis revealed that V20's dependent variable could be significantly predicted by V12 together with V16 along with V8 and V4 ($F(4, 206) = 43.314$, $p < .001$). The overall correlation between V20 and all predictor variables proves significant at the specified level.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.784	0.223		3.52	0.001
	V16	0.107	0.071	0.099	1.5	0.135
	V8	0.305	0.066	0.298	4.609	0
	V4	0.372	0.067	0.395	5.545	0
	V12	0.013	0.072	0.013	0.186	0.853
a. Dependent Variable: V20						

A coefficients table revealed that V8 (B = .305, SE = .066, $p < .001$) and V4 (B = .372, SE =

.067, $p < .001$) produced statistically significant prediction of V20. And V16 and V12 demonstrated insignificant correlations with V20 because their significance values were .135 and .853. The results for the constant indicated statistical significance (B = .784, p = .001).

Bootstrap for Coefficients							
Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	0.784	0.006	0.211	0.001	0.399	1.233
	V16	0.107	0	0.076	0.169	-0.046	0.246
	V8	0.305	0.002	0.071	0.001	0.168	0.452
	V4	0.372	0.005	0.088	0.001	0.2	0.545
	V12	0.013	-0.01	0.097	0.897	-0.192	0.186
a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples							

Results from bootstrapped coefficient analysis showed V8 ($B = .305$, $p < .001$, 95% CI [.168,

.452] significantly predicted the dependent variable and so did V4 ($B = .372$, $p < .001$, 95% CI [.200, .545]. The confidence intervals built around V16 and V12 boundaries included zero values indicating their effects were not significant following bootstrapping.

Discussion

This research study delivers essential information that describes how the investigated variables connect to each other. The descriptive statistics showed that participants gave moderate ratings on each variable while V16 and V20 received slightly higher mean scores of 3.36. The strongest correlation between V4 and V20 emerged as ($r = .609$) $p < .01$ alongside significant positive outcomes for all predictor variables (V4 V8 V16 and V12). This means V4 potentially serves as a primary factor for V20. The analysis through regression yielded statistical significance for the entire model while it explained 45.7% of the variation in V20 ($R^2 = .457$, $p < .001$). All variables did not contribute to the model to the same extent. The predictive values found through regression analysis showed V8 ($B = .305$, $p < .001$) and V4 ($B = .372$, $p < .001$) as primary predictors of V20 due to their significant impact on the variable. The analysis found no significance for V16 or V12 because their confidence intervals included zero and they exceeded the established p-value of .05. Research data indicates that V4 and V8 serve as key indicators for V20 measurements possibly because they represent fundamental behavioural characteristics and perceptual aspects of the construct. Cronbach's alpha value of .908 indicates high reliability of this measurement instrument thus improving the credibility of the research outcomes. Bootstrapping techniques added reliability to the model predictions by reducing sample bias effects which confirmed the durability of major statistical results. The study analysis shows important determinants affecting V20 and provides practical guidance for intervention planning and behavioural outcome examination of V4 and V8. Research should investigate the reason why V16 and V12 missed significant prediction of V20 despite their moderate relationships with other stronger predictive variables.

Implications

The findings of this study hold important implications for both theory development and practical application. This theoretical finding of how V4 and V8 considerably predict V20 supports the advancement of conceptual insights between their connected constructs. The strong relationship between these variables indicates they could function as essential elements of the theoretical model which needs better modelling and validation in academic publications. The V16 and V12 variables produced insignificant results even though their correlations matched V20 which suggests that correlation without controlling variables does not indicate causation. The obtained results necessitate researchers to re-evaluate ordering and causal relationships between variables across related theoretical models. Future theoretical models could improve their predictive power by elevating V4 and V8 importance and reassessing V12 and V16 placement because their straightforward predictive strength is weak. The research includes useful guidelines which help practitioners achieve outcome improvements related to V20. Interventional programs along with training initiatives and policy-making strategies need to strengthen V4 and V8 areas based on their substantial relationship with V20 outcomes. Development initiatives aimed at V4 and V8 variables will likely produce significant improvements to the outcome indicated by V20. The high measurement tool consistency ($\alpha = .908$) makes it dependable for practitioners to use this tool for uniform evaluations across homogeneous populations. Decision-makers can rely on the regression results because bootstrap validation strengthened their findings. The research unites empirical analysis with practical value to steer research agendas along with creating effective interventions across its target area.

Limitations of the Study

The research implementation using cross-sectional data prevents investigators from establishing causal relationships between study variables. The data demonstrates a clear connection between V4 and V8 to V20 yet it does not establish the order in which these variables affect one another. The study recorded data through self-report methods that could have incorporated unintentional response and social desirability effects. The weak but significant correlations between V12 and V16 indicate that multi-collinearity and missing interaction effects between variables could be present. Findings from this sample could be restricted in their application to different populations because of certain demographic characteristics. Future investigators should base their work on multi-time frame studies that gather information from various and growing data origins since bootstrap validation better consolidated the findings.

Acknowledgement

The authors declare that they received no external mentor or internal mentor funding, and they are thankful to their mentors for completion of this study.

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