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FARMERS' WELL-BEING LEVEL PREDICTION: A HYBRID PLS-SEM-MACHINE LEARNING APPROACH

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ABSTRACT

Well-being is a multifaceted concept that addresses the overall quality of an individual's life. The growing literature on well-being research tends to focus on establishing relationships between various independent variables and well-being outcomes rather than solely on predictive modeling. However, more evidence is still needed to accurately predict farmers' well-being (FWB) from the social capital perspective. The current study assesses how farmers' perceptions of social capital impact well-being in rural China. A survey involving 443 farmers was conducted to scrutinize this model. The study's conceptual framework is rooted in Social Capital Theory, which types bonding, bridging, and linking social capital. The study was unique because it used hybrid PLS-SEM and Machine Learning algorithm analyses. The results indicate that linking social capital significantly influences farmers' well-being. These findings are pertinent for stakeholders in the management science sector, aiding their understanding of the importance of factors for strategic planning. Methodologically, the study contributes to the management science literature by employing a rare multi-analytical approach, including Machine Learning algorithms, to investigate FWB. The model shows that the Support Vector Regression (SVR) model with a low Mean Squared Error (0.539) has vital prediction accuracy compared to the Random Forest.

Keywords: China, farmers' well-being, social capital, PLS-SEM, Machine learning

INTRODUCTION

The high poverty rate among farmers and the underdevelopment of the agricultural sector have motivated researchers and management practitioners to develop a working framework for farmers' overall well-being (World Bank, 2023). Rani et al. (2021) pointed out that social capital is a practical avenue to promote and improve the well-being of farmers, in addition to material and human capital. For instance, the mutual assistance and support among farmers in village communities, both in production and daily life, provide them a sense of belonging and security (Zhang et al., 2022). Another example is the e-commerce platform promoted in rural communities to improve farmers' professional skills and increase their overall well-being (Huang et al., 2020). Since the term social capital was coined, particularly in the 21st century, attention has steadily increased. The core of social capital lies in a network of social relationships that facilitates the provision of resources to individuals or organizations through reciprocity and trust, as articulated by Tsounis et al. (2023). Woolcock & Narayan (2000) delineated social capital based on the nature and function of relationships, categorizing it into bonding social capital (BOSC) characterized by close and homogeneous ties, bridging social capital (BRSC) marked by weak connections and heterogeneous backgrounds, and linking social capital (LKSC) with diverse contexts and vertical power relations. Rooted in human society, social capital is deemed indispensable for national and regional development, particularly impacting the well-being of farmers, as Fitzpatrick et al. (2023) highlighted.

Farmers' well-being (FWB), in this study, is farmers' comprehensive subjective evaluation of their agricultural production and rural community life. This implies that farmers assess and acknowledge the contentment in their lives (Rani et al., 2021). FWB encompasses diverse dimensions, including quality of life, physical and mental health, and interpersonal relationships (Diener & Ryan, 2008). Voukelatou et al. (2021) posit that well-being represents a process toward a better life, making it apt for gauging social progress and happiness.

Several studies have sought to comprehend the impact of diverse factors on well-being (Tan & Lee, 2022; Sood & Sharma, 2020; Pleeging et al., 2021; Cusinato et al., 2020). For instance, Tan & Lee (2022) explored the link between residential environments and well-being, while Sood & Sharma (2020) concentrated on the influence of resilience. Pleeging et al. (2021) explored the correlation between socioeconomic status and well-being, while Cusinato et al. (2020) investigated the role of psychological factors in shaping well-being. However, most of these studies predominantly examine the relationship between independent variables and well-being, without further analysis of predictability.

The escalating importance of well-being, particularly among rural farmers, necessitates an exploration of predictors in rural settings. This study investigates the influence of BOSC, BRSC, and LKSC as variables. These variables are independent factors affecting FWB, the dependent variable. The primary objective is to scrutinize the predictors of FWB in China, specifically examining the impact of BOSC, BRSC, and LKSC on FWB. Additionally, this study assesses the correlational relationship between BOSC, BRSC, LKSC, and FWB. Consequently, the conceptual model of the present study was devised to predict the influence of BOSC, BRSC, and LKSC on FWB. Prior research on well-being has commonly utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze theoretical frameworks and relationships between variables (Sood & Sharma, 2020; Yan et al., 2020). However, focusing solely on examining relationships without progressing to predict well-being levels overlooks a crucial aspect, diminishing practical implications and broader relevance. Integrating predictive elements may offer a more comprehensive understanding of well-being dynamics. The present research incorporates Woolcock & Narayan's (2000) theory to address knowledge gaps and evaluate FWB predictors. Moreover, the study aims to employ Machine Learning (ML) algorithms to authenticate the research model. The rest of the paper is structured as follows. Section II is a literature review, followed by research methodology. Section IV demonstrates the results of analyzing PLS-SEM and ML; the last section is a discussion and conclusion.

LITERATURE REVIEW

Conceptualizations of Farmers' Well-being

FWB is a multifaceted concept, and the World Health Organization defines it as a "state in which an individual can realize their potential, cope with normal stresses, work productively, and contribute to their community" (Nicholas, 2019, p. ii). Setiawina (2021) contended that the well-being of farmers is intricately tied to the functioning of their families, emphasizing that the well-being of farmer families entails the ability to meet their basic living needs.

The measurement of well-being has various perspectives. While GDP per capita has traditionally been considered a crucial indicator of a country's quality of life (Berbekova et al., 2022), the Easterlin paradox (Easterlin & O'Connor, 2022) challenges the notion that economic growth leads to increased happiness. As a result, conventional measures like GDP have faced criticism for their one-sidedness. Over the decades, there has been a growing acknowledgment of the significance of non-economic components as measures of well-being. Notably, Bhutan adopted the National Happiness Index in the 1970s as an alternative to GDP, and many countries have gradually adopted well-being as an indicator of social progress (Ugyel et al., 2023). This shift underscores a broader recognition of the importance of holistic well-being beyond purely economic considerations (Zhang et al., 2022).

According to Diener & Ryan (2008), well-being is segmented into health and longevity, work and economic status, interpersonal relationships, and social value. This implies that, beyond focusing on economic stability at the material level, well-being encompasses multiple dimensions, such as social relationships and health. Notably, social capital, essentially constituted by social relations, significantly influences the stable development of rural areas (Xu et al., 2023). As Putnam (2000) emphasized, social capital is crucial to ensuring farmers' survival and development, thereby contributing to the enhancement of FWB.

Conceptualizations of Social Capital

Bourdieu (2018) was the first to systematically formulate the term "social capital" in the early 1980s, incorporating it into a sociological theoretical framework to elucidate the influence of social relationships and networks on individuals and society (Sabet & Khaksar, 2020). Following Bourdieu's pioneering work, scholars such as Coleman, Putnam, Woolcock and Narayan further delved into comprehensive research and expansion of this concept. Over the subsequent two to three decades, social capital has witnessed extensive development and has found widespread application in economics, management, political science, and others. It has emerged as one of contemporary social science research's most prominent and debated concepts.

Various scholars have provided diverse definitions of social capital from different perspectives. For instance, Fukuyama (1996) characterized social capital as a collection of informal values or norms shared among group members, fostering cooperation. Lin (2002) conceptualized it as the resources individuals acquire through participation in organizations and social networks, encompassing information, support, and resources. Coleman (1988) posited that social capital resides in social structures comprising social networks and relationships involving trust and cooperation that facilitate social collaboration and collective action. Putnam (2000) underscored the value of social relationships and networks grounded in reciprocity. According to Ditomaso & Bian (2018), social capital originated from the relationship network between actors, embodying transferable resources within this network and among social actors. While these interpretations of social capital may be partially unified, they all underscore the notion of capital as instrumental and non-transferable social resources in a network-like structure, aiding individuals or organizations in achieving their goals.

As Rani et al. (2021) emphasized, social capital holds a significance that surpasses physical or human capital, playing a crucial role in facilitating survival and development—the absence of well-developed social capital challenges individuals in promoting and enhancing their well-being. Setiawina (2021) asserted that a critical aspect often overlooked in the failure of welfare-related programs and policies is the neglect of social capital as a vital factor. Considering the disadvantaged status of farmers, it becomes imperative to conduct research focusing on the interplay between social capital and well-being.

Social Capital and Farmers' Well-being

The factors influencing well-being are extensively explored in previous studies (Yan et al., 2020; Sood & Sharma, 2020; Tan & Lee, 2022). Yan et al. (2020) examined the impact of the psychological atmosphere, psychological ownership, and self-efficacy of middle-level managers in the Pakistani banking industry on employee performance and well-being. The results supported all assumptions except psychological ownership, providing valuable insights into these psychological factors in organizational settings. Sood & Sharma (2020) investigated the well-being of higher education students in India during the COVID-19 epidemic, highlighting resilience's significant direct and indirect predictive effects on well-being and offering practical insights for psychological health interventions. Tan & Lee (2022) explored the well-being of older adults in Malaysia, emphasizing the importance of residential environments and third places, particularly shopping, cultural, and educational-related spaces. While existing literature typically utilizes PLS-SEM to assess relationships between independent variables and well-being, it often neglects to expand the research method. Hybrid PLS-SEM-ML is underexplored for predictive testing and in-depth research on significant relationships. Moreover, though previous research recognizes diverse factors influencing well-being, the relationship between social capital and well-being, particularly in developing countries like China with a rural population exceeding 500 million (Li et al., 2023), needs to be more adequately addressed and represents a novel area of exploration.

Several prior studies from China have delved into FWB in rural areas (Cheng et al., 2022; Ding et al., 2023; Zhao et al., 2023). For instance, Zhao et al. (2023) scrutinized the impact of COVID-19 on well-being using survey data from rural households in Hubei Province, China, revealing a significant influence on rural families' happiness. Government intervention and income elasticity were identified as mitigating factors. Ding et al. (2023) explored the correlation between rural institutional performance, government trust, and farmers' subjective well-being, finding that policy trust has a minor influence in rural China. Meanwhile, institutional performance significantly impacts farmers with higher economic status and lower awareness of the urban-rural welfare gap. Cheng et al. (2022) investigated the relationship between benefit sharing and rural residents' well-being from a fairness perspective, demonstrating that benefit sharing effectively addresses unfair distribution issues, promoting continuous improvement in rural residents' well-being. While the literature mentioned above highlights the significant influence of different factors on the relationship with well-being, analyzed using PLS-SEM, these studies lack further predictive analyses to validate the hypothesized relationships. This study employs a hybrid analysis of the PLS-SEM approach to understand the relationship between FWB and its predictors comprehensively. Hair et al. (2019) asserted that PLS-SEM enables simultaneous analysis of measurement and structural models. Simultaneous analysis results from PLS-SEM, as highlighted by Legate et al. (2021), provide valuable insights. Furthermore, following the recommendation of Almarzouqi et al. (2022), this research integrates an ML model, employing decision trees, Bayesian networks, and neural network ML models to comprehensively explore relationships within the research model. The analysis uses Python, challenging previous research's conventional focus on linear relationships. Almarzouqi et al. (2022) argue that relying solely on a linear relationship may not adequately predict the complex nature of the situation.

Drawing from the preceding analysis, this study posits the following research hypotheses concerning the influence of diverse social capital forms, encompassing Bonding Social Capital (BOSC), Bridging Social Capital (BRSC), and Linking Social Capital (LKSC), on the well-being of farmers (FWB).

H1. BOSC has a positive association with FWB.

H2. BRSC has a positive association with FWB.

H3. LKSC has a positive association with FWB.

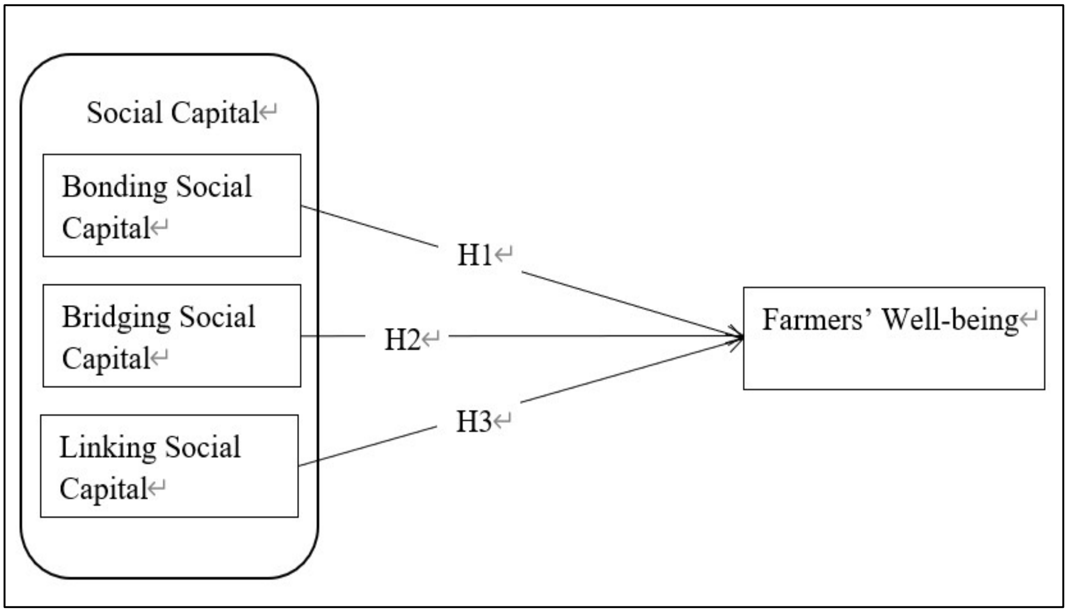

Figure 1. Structural model

RESEARCH METHODOLOGY

Guizhou Province in southwest China encompasses 92.5% of its land area as mountains and hills, resulting in a challenged ecological environment and underdeveloped infrastructure. It ranks among the country's most widespread and severely impoverished provinces (Li et al., 2022). The data for this study were sourced from self-administered questionnaires distributed among farmers in two villages within Guizhou Province, China. These villages are part of the final batch of poverty alleviation counties (Guizhou Rural Revitalization Bureau, 2020). Rigorous translation and back-translation procedures were implemented to ensure the questionnaire's linguistic accuracy. With support from village cadres, data distribution and collection occurred through the China Questionnaire Star platform. Farmers, duly informed of the study's purpose, willingly completed the questionnaire (Alharbi & Sohaib, 2021).

PLS-SEM was employed in the initial analysis phase to examine the relationship between constructs and the dependent variable. Subsequently, an ML-based analysis was conducted to complement PLS-SEM findings. Two models, random forest and support vector regression, were employed in the ML analysis and recognized for their superior accuracy compared to single analysis approaches (Alharbi & Sohaib, 2021). Detailed descriptions of the PLS-SEM and ML analyses are provided in the subsequent section.

Data Collection

This study employs a combination of convenience and random sampling techniques. The determined minimum sample size is 384 individuals, fulfilling the criteria outlined by Krejcie and Morgan tables (Krejcei & Morgan, 1970). Of the 500 distributed questionnaires, 57 farmers have yet to respond, primarily due to literacy challenges or a lack of familiarity with electronic products. Consequently, the total number of valid questionnaires collected for analysis is 443.

Personal Demographic Information

Demographic information (Table 1) shows that among a total of 443 respondents, there is a slightly higher proportion of males (52.4%), and most of the respondents (54%) are between the ages of 18 and 29. Moreover, most respondents (73.4%) have received high school education or above. Further, most respondents' annual per capita primary income (69.7%) is 5,999 yuan or less (currency: RMB).

Table 1. Demographics

Variable	**Frequency**	**(%)**
Gender		
Male	232	52.4
Female	211	47.6
Total	**443**	**100**
Age		
18-29	239	54
30-39	100	22.6
40-49	56	12.6
50-59	40	9
60 and above	8	1.8
Total	**443**	**100**
Degree of Education		
Middle School and below	118	26.6
High School and above	325	73.4
Total	**443**	**100**
Average annual primary income of household members (currency: RMB)		

5999 and below	309	69.7
6000-7999	47	10.6
8000-9999	23	5.2
10000-11999	26	5.9
12000 and above	38	8.6
Total	**443**	**100.0**

Study Instrument

The items for measuring variables are mature scales validated from previous studies. The measurement of BOSC is adopted and modified from the scale of Williams (2006). For measuring BRSC, items come from Williams (2006) and Hwang & Kim (2015). Regarding the measurement of LKSC, items from Liu & Pan (2020), Zhang & Jiang (2019), and Ben-Hador et al. (2021) were used. For assessing FWB, seven items were adopted from (Chakrabarti et al., 2020). This study has made corresponding adjustments considering the differences in research background and cultural understanding. This scale ranged from a response of strongly disagree (1) to agree (5) strongly.

A Pilot Study of the Questionnaire

To gauge the questionnaire's reliability, this study conducted pilot studies with 33 participating farmers. The internal reliability of the study was assessed using Cronbach's alpha (CA) value in SPSS.

RESULTS

PLS-SEM Results

Convergent Validity

This study assesses the model's convergence effectiveness through critical indicators, including indicator loading, Cronbach alpha value (CA), Comprehensive Reliability (CR), and average variance extracted (AVE). As depicted in Table 2, the values of CA and CR range from 0.871 to 0.920, surpassing the established standard of 0.70 (Hair et al., 2019), indicating satisfactory indicator reliability. The average variance extracted (AVE) for the model in this study falls between 0.512 and 0.613, exceeding the 0.5 threshold. Moreover, the indicator loading surpasses 0.6 (Hair et al., 2019). Therefore, the measurement model of this study achieved convergence effectiveness. However, when evaluating the effectiveness of convergence, some items below the threshold were deleted. Furthermore, it is noteworthy that the Variance Inflation Factor (VIF) for item LKSC4 in the model of this study is the highest, registering at 3.465. Importantly, this value is below the established threshold of 5. Consequently, there is no collinearity issue in this study.

Table 2. Reliability and convergent validity

Structure	Items	Loadings	VIF	CA	rho_A	CR	AVE
BOSC	BOSC1	0.731	1.916	0.871	0.874	0.899	0.527
	BOSC10	0.752	1.919				
	BOSC2	0.774	2.193				
	BOSC4	0.634	1.465				
	BOSC5	0.754	1.843				
	BOSC6	0.721	1.631				
	BOSC7	0.729	1.785				
	BOSC8	0.704	1.614				
BRSC	BRSC1	0.691	1.965	0.905	0.907	0.920	0.512
	BRSC10	0.697	1.643				
	BRSC11	0.720	2.063				
	BRSC12	0.693	1.916				
	BRSC2	0.750	2.269				
	BRSC3	0.703	2.103				
	BRSC4	0.744	2.236				
	BRSC6	0.767	2.125				
	BRSC7	0.701	1.729				
	BRSC8	0.657	1.689				
	BRSC9	0.741	2.288				
LKCS	LKSC1	0.804	2.428	0.892	0.894	0.916	0.613
	LKSC2	0.842	3.025				

	LKSC3	0.831	3.301				
	LKSC4	0.845	3.465				
	LKSC5	0.823	2.338				
	LKSC6	0.678	1.973				
	LKSC7	0.627	1.805				
FWB	FWB1	0.789	2.059	0.889	0.890	0.913	0.600
	FWB2	0.769	2.091				
	FWB3	0.826	2.456				
	FWB4	0.809	2.388				
	FWB5	0.755	1.997				
	FWB6	0.713	1.808				
	FWB7	0.756	2.060				

Discriminant Validity

In evaluating the discriminant validity of the model, this study employed the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Examination of Table 3 reveals that the square roots of the Average Variance Extracted (AVE) values for all constructs have been cross-checked, and the off-diagonal values are observed to be smaller than the corresponding diagonal (bold) values, as required. Furthermore, the HTMT values presented in Table 3 are below the stipulated threshold of 0.85, as Henseler et al. (2016) recommended. Consequently, it can be affirmed that the discriminant validity of this research model has been substantiated.

Table 3. Discriminant validity

	Fornell and Larcker criteria				HTMT			
Structure	BOSC	BRSC	FWB	LKSC	BOSC	BRSC	FWB	LKSC
BOSC	**0.726**							
BRSC	0.547	**0.715**			0.623			
FWB	0.497	0.406	**0.775**		0.552	0.433		

LKSC	0.425	0.487	0.505	**0.783**	0.486	0.538	0.563

Hypotheses Testing employing PLS-SEM

This study assessed the structural model's interdependence using PLS-SEM. The R^2 value, indicating the model's predictive ability, is 0.355 (see Table 4), signifying a commendable performance. Table 4 also presents the p-values and t-values, with all values falling below 0.01 and 0.05, strongly supporting the research hypotheses. The first hypothesis is substantiated, revealing a significant correlation between BOSC and FWB. However, the second hypothesis was invalid, indicating no positive correlation between BRSC and FWB (ß=0.070, t=1.270, p=0.102). On the other hand, empirical data supports the third hypothesis, indicating a statistically significant relationship between LKSC and FWB.

Table 4. Hypotheses testing

Relationships	Beta	S.D	t-value	p-value	f^2	R^2	Decision
BOSC -> FWB	0.315	0.052	6.026	0.000	0.103		Supported
BRSC -> FWB	0.070	0.055	1.270	0.102	0.005	0.355	Not Supported
LKSC -> FWB	0.337	0.051	6.657	0.000	0.128		Supported

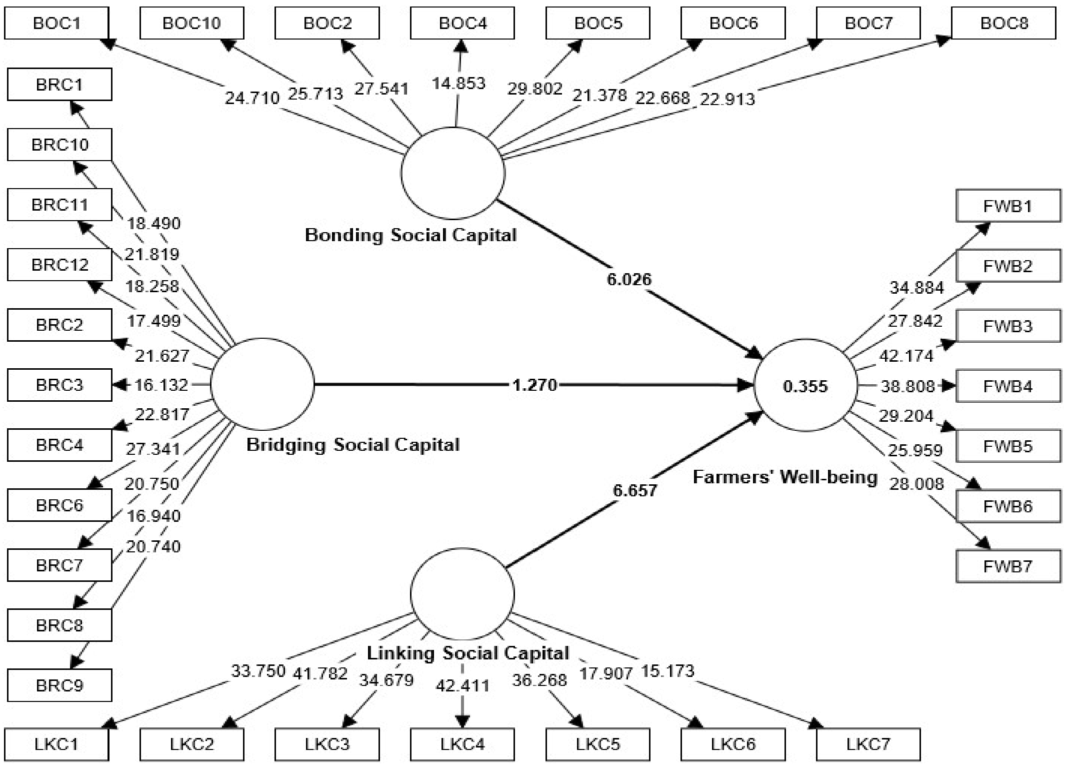

Figure 2. Structural model

The detection indicator for predictive power of structural model is PLSpredict (Hair et al., 2019). The values of the indicator "RMSE" in Table 5 indicate that the model in this study has high predictive power.

Table 5. PLSpredict

Focal Constructs	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	PLS-SEM-LM	
						RMSE	MAE
FWB1	0.222	0.954	0.739	0.980	0.745	-0.026	-0.006
FWB2	0.208	1.020	0.834	1.049	0.829	-0.029	0.005

FWB3	0.178	1.042	0.825	1.080	0.848	-0.038	-0.023
FWB4	0.183	1.050	0.873	1.057	0.836	-0.007	0.037
FWB5	0.114	1.135	0.945	1.163	0.925	-0.028	0.020
FWB6	0.253	0.895	0.699	0.919	0.676	-0.024	0.023
FWB7	0.210	0.921	0.720	0.958	0.725	-0.037	-0.005

Machine Learning Analysis

In the second step of the analysis, ML complements the PLS-SEM findings, emphasizing each predictor's factor relevance. ML demonstrates superior prediction accuracy compared to SEM, owing to its capacity to assess linear or non-linear relationships (Torres et al., 2023). The ML analysis using the following component: The ML analysis consists of inputs training data, features, Algorithm, Model, Training, Testing, Prediction, Target, Loss Function, and Hyperparameter. In this study, ML analysis recommendations, as outlined by Torres et al. (2023), were adhered to despite the application of ML analysis, as indicated by Muzumdar et al. (2022). Adopting ML analysis offers improved decision-making, enhanced engagement, and consideration of individual sentiments and needs (Nour et al., 2020). The ML analysis incorporates the Rectified Linear Unit (ReLU) function as the activation function for both input and output, ensuring optimal ML performance by normalizing the range between 0 and 1. The ML model comprises four input factors—BOSC, BRSC and LKSC—culminating in one output, FWB. The Mean Squared Error (MSE) was calculated for both testing (20%) and training (80%) datasets, with Table 6 presenting the results. Lower MSE values indicate higher predictive accuracy (Alshboul et al., 2022). Additionally, following analysis (Muzumdar et al., 2022), sensitivity analysis was conducted to determine the relative importance of each input— BOSC, BRSC and LKSC. The findings reveal that Linking is the foremost predictor in predicting FWB, with Bonding emerging as the second significant predictor, while BRSC exhibits a comparatively weaker impact. The regression model has been successfully fitted to predict the 'FWB' score based on the BOSC, BRSC, and LKSC variables. The Mean Squared Error (MSE) and R-squared Score are provided, along with the coefficients for each feature, indicating their relative importance in the model. The visualization of the actual FWB versus the predicted FWB is shown in Figure 3.

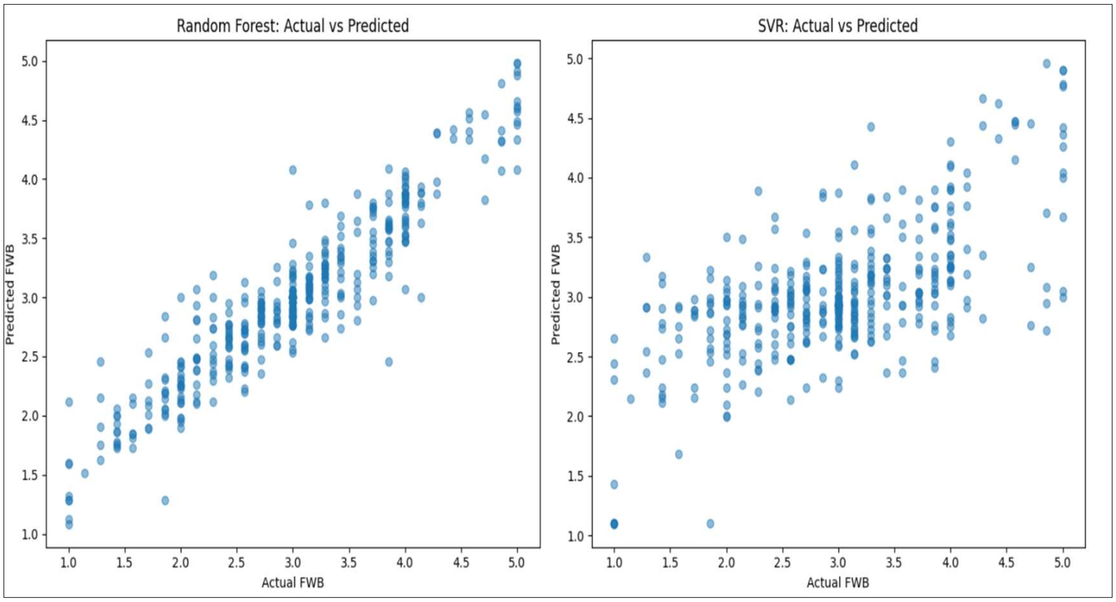

Figure 3. Cross-Validation Score

The Random Forest model has a mean MSE of 0.619 with a standard deviation of 0.091, while the SVR model has a mean MSE of 0.540 with a standard deviation of 0.075. The scatter plots show the actual vs. predicted 'FWB' scores for both models, providing a visual comparison of their performance. The results show that the Support Vector Regression (SVR) model has a slightly lower mean, Mean Squared Error (MSE) compared to the Random Forest model, indicating a better fit to the data on average. The standard deviation of the MSE is also lower for the SVR model, suggesting that its performance is more consistent across different cross-validation folds. The visualization compares the actual versus predicted 'FWB' scores for both models, with each point representing an observation in the dataset.

Table 6. ML Performance

s/n	ML Algorithms	Mean (MSE)	Std
1	Random Forest	0.619695331458518	0.09147475661956292
2	Support Vector Regression	0.5399803402508463	0.0752367307440891

DISCUSSION AND CONCLUSION

Theoretical and Practical Implications

The study innovatively integrated PLS-SEM and ML algorithms to evaluate the research model. This pioneering hybrid approach holds substantial implications for the management research domain, marking a distinctive initiative in using ML algorithms for predicting FWB within a managerial context. Prior research, such as Rakhra et al. (2022), has demonstrated PLS-SEM's ability to predict dependent variables and validate conceptual models. Concurrently, Alharbi and Sohaib (2021) highlight ML's proficiency in predicting dependent variables based on independent variables. This study distinguishes itself through a comprehensive ML approach, utilizing Random Forest (RF) and Support Vector Regression (SVR). Significantly, SVR demonstrated superior performance over RF, with a classification strategy dividing the sample based on key predictors, aligning with Almarzouqi et al.'s (2022) recommendations—the non-parametric PLS-SEM method assessed coefficient significance. SVR showcased higher predictive accuracy than both RF and PLS-SEM models, attributed to its architecture's capability to unravel intricate relationships among variables.

Managemental Implications

The findings of the present research significantly impact management science, revealing that bonding and linking have a substantial influence on FWB. However, the study found that BRSC did not significantly influence with FWB. Thus, policymakers should focus on promoting BRSC to improve farmers' quality of life. Subsequent research endeavors should explore the influence of various demographic groups across diverse geographical contexts.

Limitations and Suggestions for Future Studies

While contributing to management science literature, the present research has inherent limitations. The conceptual model is constrained as it solely relies on social capital, utilizing constructs from social capital theory— BOSC, BRSC, and LKSC. Despite the significance of these aspects, the study overlooks other constructs, like psychological factors, potentially impacting the model (Chipfupa & Tagwi, 2021). The online questionnaire distribution also introduces a potential response bias (Helen, 2019). Generalizability is limited, specifically to settings beyond farmers, as the study exclusively focuses on the agricultural sector.

Conclusion

This paper adopts a unique hybrid PLS-SEM and machine learning algorithm to evaluate the impact of rural social capital in China, including bonding, bridging, and linking, on farmers' well-being, and to accurately predict farmers' well-being. The results indicate that bonding and linking closely influence FWB while bridging does not significantly impact it. ML analysis further reveals that bonding and linking are predictors of FWB. Interestingly, the Support Vector Regression ML model demonstrates higher predictive accuracy than the Random Forest ML model. These results align with findings from other studies (Clausen et al., 2019; Murgaš et al., 2022).

References

- Alharbi, A., & Sohaib, O. (2021). *Technology Readiness and Cryptocurrency Adoption : PLS-SEM and Deep Learning Neural Network Analysis*. *9*. https://doi.org/10.1109/ACCESS.2021.3055785
- Almarzouqi, A., Aburayya, A., & Salloum, S. A. (2022). Prediction of User ' s Intention to Use Metaverse System in Medical Education : A Hybrid SEM-ML Learning Approach. *IEEE Access*, *10*, 43421–43434. https://doi.org/10.1109/ACCESS.2022.3169285
- Alshboul, O., Shehadeh, A., & Almasabha, G. (2022). *Extreme Gradient Boosting-Based Machine Learning Approach for Green Building Cost Prediction*.
- Ben-Hador, B., Eckhaus, E., & Klein, G. (2021). Personal Social Capital in Organizations: A New Scale to Assess Internal and External Personal Social Capital in Organizations. *Social Indicators Research*, *157*(3), 1155–1177. https://doi.org/10.1007/s11205-021-02702-x
- Berbekova, A., Muzaffer Uysal, & A. George Assaf. (2022). Toward an Assessment of Quality of Life Indicators as Measures of Destination Performance. *Journal of Travel Research*, *61*(6), 1424–1436. https://doi.org/https://doi.org/10.1177/00472875211026755
- Bourdieu, P. (2018). The forms of capital. *The Sociology of Economic Life, Third Edition*, 78–92. https://doi.org/10.4324/9780429494338
- Chakrabarti, A., Handa, S., Angeles, G., & Seidenfeld, D. (2020). A cash plus program reduces youth exposure to physical violence in Zimbabwe. *World Development*, *134*, 105037. https://doi.org/10.1016/j.worlddev.2020.105037
- Cheng, X., Wang, J., & Chen, K. Z. (2022). Does villager social capital hinder poverty targeting? Evidence from poverty-stricken county of Western China. *China Economic Review*, *71*, 101728. https://doi.org/10.1016/j.chieco.2021.101728
- Chipfupa, U., & Tagwi, A. (2021). Youth's participation in agriculture: A fallacy or achievable possibility? Evidence from rural South Africa. *South African Journal of Economic and Management Sciences*, *24*(1), 1–12. https://doi.org/10.4102/sajems.v24i1.4004
- Clausen, T., Meng, A., & Borg, V. (2019). Does Social Capital in the Workplace Predict Job Performance, Work Engagement, and Psychological Well-Being? A Prospective Analysis. *Journal of Occupational and Environmental Medicine*, *61*(10), 800–805. https://doi.org/10.1097/JOM.0000000000001672
- Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*, *94*, S95–S120. https://www.jstor.org/stable/2780243
- Cusinato, M., Iannattone, S., Spoto, A., Poli, M., Moretti, C., Gatta, M., & Miscioscia, M. (2020). Stress, resilience, and well-being in Italian children and their parents during the COVID-19 pandemic. International Journal of Environmental Research and Public Health

[revista en Internet] 2020 [acceso 2 de noviembre de 2022]; 17(22): 1-17. *International Journal of Environmental Research and Public Health*, *22*(17), 8297. https://doi.org/doi:10.3390/ijerph17228297

- Diener, E., & Ryan, K. (2008). *Subjective well-being : a general overview*. *39*(4), 391–406.
- Ding, X., Lu, Q., Li, L., Sarkar, A., & Li, H. (2023). Evaluating the Impact of Institutional Performance and Government Trust on Farmers' Subjective Well-Being: A Case of Urban–Rural Welfare Gap Perception and Family Economic Status in Shaanxi, Sichuan and Anhui, China. *International Journal of Environmental Research and Public Health*, *20*(1). https://doi.org/10.3390/ijerph20010710
- Ditomaso, N., & Bian, Y. (2018). *The Structure of Labor Markets in the US and China : Social The Structure of Labor Markets in the US and China : Social Capital and Guanxi*. *May*. https://doi.org/10.1017/mor.2017.63
- Easterlin, R. A., & O'Connor, K. J. (2022). The Easterlin Paradox. In *Handbook of labor, human resources and population economics* (pp. 1–25). Springer International Publishing.
- Fitzpatrick, E., Baycan, T., & Akgüngör, S. (2023). Social capital and rural development: an introduction to the special issue. *Annals of Regional Science*, *70*(3), 603–609. https://doi.org/10.1007/s00168-023-01222-5
- Fukuyama, F. (1996). *Trust: The social virtues and the creation of prosperity*. Simon and Schuster.
- Guizhou Rural Revitalization Bureau. (2020). *The last 9 poverty-stricken counties in Guizhou Province announced their official withdrawal from the poverty county sequence*. http://gz.people.com.cn/n2/2020/1123/c222152-34432705.html
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
- Helen, B. (2019). *About Research: Online Surveys*.
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, *116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382
- Huang, C.-C., Jin，Huiying, Zhang，Jieyou, Zheng，Qinqin, Chen，Yafan, Cheung，Shannon, & Liu，Chuwei. (2020). The effects of an innovative e-commerce poverty alleviation platform on Chinese rural laborer skills development and family well-being. *Children and Youth Services Review*, *116*, 105189. https://doi.org/https://doi.org/10.1016/j.childyouth.2020.105189
- Hwang, H., & Kim, K. (2015). *Social media as a tool for social movements : the effect of social media use and social capital on intention to participate in social movements*. *39*, 478–488. https://doi.org/10.1111/ijcs.12221
- Krejcei, R., & Morgan, D. (1970). Determining Sample Size for Research. *Educational and Psychological Measurement Duluth: University of Minesota*.
- Legate, A. E., Jr, J. F. H., Chretien, J. L., & Risher, J. J. (2021). PLS-SEM : Prediction-

oriented solutions for HRD researchers. *Human Resource Development Quarterly*, *34*(1), 1–19. https://doi.org/10.1002/hrdq.21466

- Li, G., Jiao, Y., Li, J., & Yan, Q. (2022). Spatiotemporal Evolution and Influential Factors of Rural Poverty in Poverty-Stricken Areas of Guizhou Province : Implications for Consolidating the Achievements of Poverty Alleviation. *ISPRS International Journal of Geo-Information*, *11*(11), 546. https://doi.org/https:// doi.org/10.3390/ijgi11110546
- Li, W., Yu, Y., He, Q., Xu, D., Qi, Y., & Deng, X. (2023). Impact of clean energy use on the subjective health of household members: Empirical evidence from rural China. *Energy*, *263*, 126006. https://doi.org/https://doi.org/10.1016/j.energy.2022.126006
- Lin, N. (2002). *Social capital: A theory of social structure and action (Vol. 19)*. Cambridge university press.
- Liu, Q., & Pan, H. (2020). Investigation on life satisfaction of rural-to-urban migrant workers in China: A moderated mediation model. *International Journal of Environmental Research and Public Health*, *17*(7). https://doi.org/10.3390/ijerph17072454
- Murgaš, F., Petrovič, F., & Tirpáková, A. (2022). Social Capital as a Predictor of Quality of Life: The Czech Experience. *International Journal of Environmental Research and Public Health*, *19*(10). https://doi.org/10.3390/ijerph19106185
- Muzumdar, P., Basyal, G. P., & Vyas, P. (2022). An Empirical Comparison of Machine Learning Models for Student's Mental Health Illness Assessment. *Asian Journal of Computer and Information Systems*, *10*(1), 1–10. https://doi.org/10.24203/ajcis.v10i1.6882
- Nicholas, B. J. (2019). *What is wellbeing? An examination of the World Health Organisation's definition of wellbeing in Australian university students with depressive symptoms*.
- Nour, M., Sindi, H., & Polat, K. (2020). *The Effect of Training and Testing Process on Machine Learning in Biomedical Datasets*. *2020*.
- Pleeging, E., Burger, M., & van Exel, J. (2021). The Relations between Hope and Subjective Well-Being: a Literature Overview and Empirical Analysis. *Applied Research in Quality of Life*, *16*(3), 1019–1041. https://doi.org/10.1007/s11482-019-09802-4
- Putnam, R. D. (2000a). *Bowling alone: The collapse and revival of American community*. Simon and schuster.
- Putnam, R. D. (2000b). *Bowling alone: The collapse and revival of American community*. Simon and schuster.
- Rakhra, M., Sanober, S., Quadri, N. N., Verma, N., Ray, S., & Asenso, E. (2022). Implementing Machine Learning for Smart Farming to Forecast Farmers' Interest in Hiring Equipment. *Journal of Food Quality*, *2022*. https://doi.org/10.1155/2022/4721547
- Rani, A., Quddoos, A., Yaseen, M. R., Tabassum, S., & Asif, A. (2021). The Impact of Social Capital on Household Well-being in Pakistan. *Social Indicators Research*, *158*(3), 927–946. https://doi.org/10.1007/s11205-021-02717-4
- Sabet, N. S., & Khaksar, S. (2020). The performance of local government , social capital

and participation of villagers in sustainable rural development. *The Social Science Journal*, *00*(00), 1–29. https://doi.org/10.1080/03623319.2020.1782649

- Setiawina, N. D. (2021). *FARMERS ' INSTITUTIONS AND SOCIAL CAPITAL IN IMPROVING THE WELFARE OF CHILI FARMERS*. *5*(03), 222–235.
- Sood, S., & Sharma, A. (2020). Resilience and Psychological Well-Being of Higher Education Students During COVID-19: The Mediating Role of Perceived Distress. *Journal of Health Management*, *22*(4), 606–617. https://doi.org/10.1177/0972063420983111
- Tan, T. H., & Lee, J. H. (2022). Residential environment, third places and well-being in Malaysian older adults. *Social Indicators Research*, *162*(2), 721–738. https://doi.org/10.1007/s11205-021-02856-8
- Torres, M. E. C., Pablo Marcelo Vargas-Piérola, Carlos F. Pinto, & Rubén Alvarado. (2023). Multiple sequential mediation model of the effect of Social Capital Investment on Academic Stress. *International Journal of Educational Research Open*, *5*(June). https://doi.org/10.1016/j.ijedro.2023.100259
- Tsounis, A., Xanthopoulou, D., Demerouti, E., Kafetsios, K., & Tsaousis, I. (2023). Workplace Social Capital: Redefining and Measuring the Construct. *Social Indicators Research*, *165*(2), 555–583. https://doi.org/10.1007/s11205-022-03028-y
- Ugyel, L., Givel, M., & Chophel, D. (2023). *Punctuating " Happiness": Punctuated equilibrium theory and the agenda-setting of the Gross National Happiness (GNH) policy in Bhutan*. *March*, 1–17. https://doi.org/10.1111/ropr.12559
- Voukelatou, V., Gabrielli, L., Miliou, I., Cresci, S., Sharma, R., Tesconi, M., & Pappalardo, L. (2021). Measuring objective and subjective well-being: dimensions and data sources. In *International Journal of Data Science and Analytics* (Vol. 11, Issue 4). Springer International Publishing. https://doi.org/10.1007/s41060-020-00224-2
- Williams, D. (2006). On and off the 'Net: Scales for Social Capital in an Online Era. *Journal of Computer-Mediated Communication*, *11*(2), 593–628. https://doi.org/10.1111/j.1083-6101.2006.00029.x
- Woolcock, M., & Narayan, D. (2000). Social capital: Implications for development theory, research, and policy. *World Bank Research Observer*, *15*(2), 225–249. https://doi.org/10.1093/wbro/15.2.225
- World Bank. (2023). *The high poverty rate among farmers and underdevelopment of the agricultural sector*. https://press.un.org/en/2023/gaef3590.doc.htm
- Xu, H., Zhang, C., & Huang, Y. (2023). Social trust, social capital, and subjective well-being of rural residents: micro-empirical evidence based on the Chinese General Social Survey (CGSS). *Humanities and Social Sciences Communications*, *10*(1). https://doi.org/10.1057/s41599-023-01532-1
- Yan, R., Farhan Basheer, M., Irfan, M., & Naveed, R. T. (2020). Role of Psychological factors in Employee Well-being and Employee Performance: An Empirical Evidence from Pakistan. *Revista Aregentina de Clincica Psciologica*, *xxix*(November), 638–650. https://doi.org/10.24205/03276716.2020.1060

- Zhang, J., Xie, J., Zhang, X., & Yang, J. (2022). Income , Social Capital , and Subjective Well-Being of Residents in Western China. *Sustainability*, *14*(15), 9141. https://doi.org/https://doi.org/10.3390/su14159141
- Zhang, Y., & Jiang, J. (2019). Social Capital and Health in China: Evidence from the Chinese General Social Survey 2010. *Social Indicators Research*, *142*(1), 411–430. https://doi.org/10.1007/s11205-018-1907-2
- Zhang, Y., Liu, G., Ma, Z., Deng, X., Song, J., & Xu, D. (2022). The Influence of Land Attachment on Land Abandonment from the Perspective of Generational Difference: Evidence from Sichuan Province, China. *International Journal of Environmental Research and Public Health*, *19*(18). https://doi.org/10.3390/ijerph191811651
- Zhao, F., Cui, Z., Zhao, X., & Liu, W. (2023). Did COVID-19 affect rural households' subjective well-being? A social survey from rural China. *International Journal of Disaster Risk Reduction*, *92*, 103736. https://doi.org/https://doi.org/10.1016/j.ijdrr.2023.103736