METHODOLOGICAL AND PRACTICAL ADVANTAGES OF PLS-SEM IN MANAGEMENT RESEARCH: THE CASE OF RAKIJA

Slobodan Adžić[1], Doloris Bešić-Vukašinović[2], Ivana Savić[3]
Corresponding author E-mail: sadzic@akademijahtw.bg.ac.rs

A R T I C L E I N F O

A B S T R A C T

Structural equation modeling (SEM) is widely applied in consumer behavior research; however, the methodological choice between covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) remains contested in applied research contexts. This study compares the performance of CB-SEM and PLS-SEM using an identical theoretical model previously employed to analyze cultural factors influencing consumer purchasing behavior for rakija, a culturally embedded agricultural product. Survey data were reanalyzed using SmartPLS, focusing on measurement model evaluation and the estimation of direct and indirect structural effects. The results show that PLS-SEM yields lower path coefficient estimates but higher explained variance (R²) compared to CB-SEM, indicating more conservative effect estimation alongside stronger explanatory performance. These findings suggest that PLS-SEM represents a methodologically appropriate and practically advantageous approach for modeling consumer behavior in culturally specific agricultural markets. The study contributes to the applied SEM literature by providing empirical guidance on method selection in agricultural economics research.

Introduction

This study focuses on the practical implementation of structural equation modeling (SEM) using SmartPLS (Ringle et al., 2024). The objective was to highlight the

1   Slobodan Adžić, Ph.D., Full Professor, Academy of Hospitality, Tourism, and Wellness, Tošin Bunar 179đ, 11070 Belgrade, Serbia, Phone: 381 11 4561375, E-mail: sadzic@akademijahtw.bg.ac.rs, ORCID ID (https://orcid.org/0000-0002-8827-5492)

2   Doloris Bešić-Vukašinović, Ph.D., Lecturer, Academy of Technical and Art Applied Studies, Textile School for Design, Technology and Management, Starine Novaka 24, 11000 Belgrade, Serbia, Phone: +381 64 194 888 6, E-mail: doloris.besic@yahoo.com, ORCID ID (https://orcid.org/0000-0001-6763-9747)

3   Ivana Savić, PhD student, University of Adriatik, Faculty of Management Herceg Novi, Zemunska 143 street, 85348 Meljine, Montenegro, E-mail: ivana.s7895@gmail.com, Phone: +381 61 48 88 680, ORCID ID (https://orcid.org/0009-0006-3458-0009)

methodological advantages of Partial Least Squares Structural Equation Modeling (PLS-SEM) compared to Covariance-Based Structural Equation Modeling (CB-SEM) and to address its shortcomings. The modules of PLS-SEM in SmartPLS are explained using a previously published CB-SEM model that investigated the cultural factors influencing consumer purchasing behavior related to rakija (Adžić, 2025). This traditional plum brandy was recognized as an intangible cultural heritage by UNESCO under the title "Social practices and knowledge related to the production and use of traditional plum brandy – šljivovica" at the end of 2022 (UNESCO, 2022).

Although both CB-SEM and PLS-SEM methodologies were introduced around the same period, CB-SEM gained significantly greater adoption because of its initial accessibility via LISREL software in the late 1970s and AMOS in the 2000s. The introduction of SmartPLS 2 in 2005 led to a substantial increase in PLS-SEM utilization (Hair et al., 2024). SmartPLS is increasingly recognized as a robust alternative to AMOS for structural equation modeling, particularly because of its user-friendly interface and advanced reporting features, which enhance accessibility for researchers (Wong, 2013).

A key conceptual difference between PLS-SEM and CB-SEM lies in how latent variables are handled in the model. CB-SEM is a common factor-based structural equation modeling method that interprets constructs as common factors that explain the covariation among their associated indicators (Hair et al., 2021). In contrast, PLS-SEM asserts that the constructs of interest can be measured as composites, which classifies it as a composite-based structural equation modeling approach (Hwang et al., 2020). CB-SEM is mainly used to confirm or challenge theoretical frameworks composed of systematic relationships among different variables that can be empirically tested. This validation process assesses the accuracy of the proposed theoretical model in predicting the covariance matrix of a specific sample dataset (Hair et al., 2021).

To enhance the fit of models in CB-SEM, researchers often limit the number of indicators associated with each construct, which consequently increases uncertainty (Hair et al., 2021). PLS-SEM provides higher statistical power and can yield results when CB-SEM encounters convergence issues or fails to achieve model fit. The measurement model estimates (loadings) in PLS-SEM tend to be greater, whereas the structural model estimates (path coefficients) are comparatively lower than those derived from CB-SEM (Reinartz et al., 2009). PLS-SEM utilizes ordinary least squares regression to achieve the goal of maximizing the R^2 values of the endogenous constructs (Hair et al., 2024). Because PLS-SEM is grounded in total variance, the Average Variance Extracted (AVE) values are consistently higher than those in CB-SEM, rendering the R^2 value in PLS-SEM a more significant predictor of the variance captured by the indicators of the endogenous constructs than the R^2 value in CB-SEM.

Materials and methods

The author conducted a thorough review of academic journals and validated research scales related to various alcoholic beverages using the Business Source Premier

database for the first study in December 2023 (Adžić, 2025). This study was prompted by the absence of specifically designed scales for rakija in the existing literature. By searching for "alcohol" and "consumer," 56 unique articles were identified and retrieved after eliminating the duplicates. These articles formed the foundation for analyzing and adapting five research scales for the current study and assisted in developing a structural equation model.

Cultural impact of rakija (CIR) scale (Yap & Nan Chen, 2017): (1) Rakija consumption is common in my community, (2) Rakija is a key part of my culture, (3) Rakija tastes good, and (4) Rakija is healthy.

Level of consumer involvement (LCI) scale (Calvo-Porral et al., 2020): (1) beer is significant to me, (2) I have a strong interest in beer, and (3) beer matters to me, rated on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The scale demonstrated internal reliability, with Cronbach's alpha values exceeding .70. The term "beer" will be substituted with "rakija."

Factors to purchase rakija (FPR) scale (Kruger & Viljoen, 2022): (1) recommendations from friends, (2) celebrity endorsements, (3) advertising, (4) positive reviews, (5) sampling at events, (6) advice from liquor store staff, (7) attractive pricing, and (8) distillery visits.

Attitudes toward rakija (ATR) scale (Spears & Singh, 2004): (1) unappealing/appealing, (2) bad/good, (3) unpleasant/pleasant, (4) unfavorable/favorable, and (5) unlikable/likable.

Rakija purchase intentions (RRI) scales (Spears & Singh, 2004): (1) never/definitely, (2) definitely do not intend to buy/definitely intend, (3) very low/high purchase interest, (4) definitely not buy it/definitely buy it, and (5) probably not/probably buy it.

The survey data was evaluated using SmartPLS version 4.1.1.2.

Results

CB-SEM model results

The primary aim of the published CB-SEM research (Adžić, 2025) was to develop a comprehensive latent structural equation model to investigate the cultural factors affecting consumer purchasing behaviors related to rakija, a culturally significant alcoholic beverage in Serbia. The secondary aim was to qualitatively evaluate the model's appropriateness for examining alcoholic beverages that are specific to certain cultures and recognized nationally, as opposed to those that are universally applicable to all cultures. The key outcome of this study revealed that culture plays a substantial role in shaping consumer behavior and purchasing patterns concerning this national drink, both directly and indirectly through various mediators. Furthermore, the findings from the multigroup analysis indicated a significant difference between the group of rakija consumers who favored this culturally and nationally recognized drink and those

who continued to prefer beer. The hypothesis concerning the direct impact of culture on national alcoholic beverage purchases is well-established and has been explored in previous studies (Prendergast et al., 2010).

Figure 1. CB-SEM
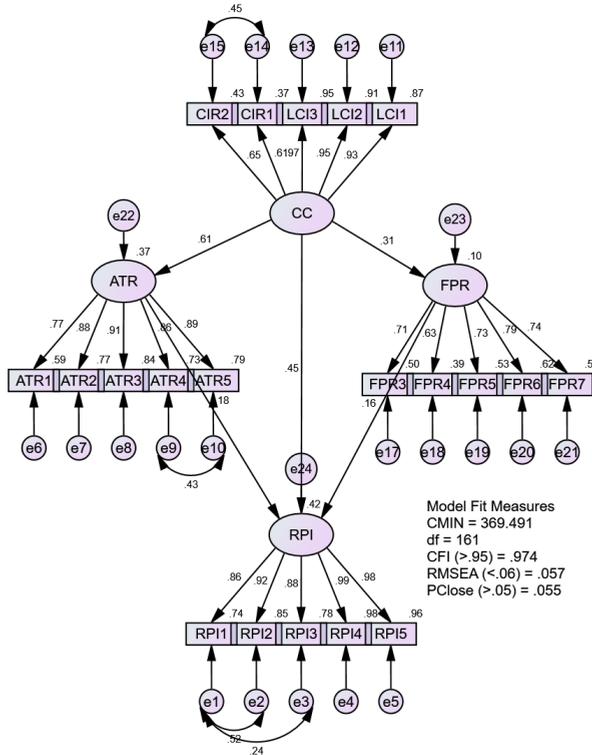

Source: Adžić (2025)

Therefore, this CB-SEM approach aimed to quantify the strength of the relationships in the model, especially in the context of rakija purchase intentions (Figure 1). Finally, all elements within the model explained .42 of the variance in consumer purchasing intentions. The direct impact of culture on the intention to purchase rakija of .45 was measured. Additionally, the model demonstrated a significant effect size, with the total direct and indirect effects of culture reaching as high as .61. Moreover, all the path coefficients were statistically significant.

Establishing PLS-SEM model

The next step was to establish a PLS-SEM model. In accordance with the characteristics of the PLS-SEM model, our objective was to achieve the highest possible R^2 while attaining statistical significance. As we do not have to achieve model fit, the model will contain all five latent variables with all the original 25 measured variables, unlike our CB-SEM model, where, because of reaching model fit, the number of measured

variables was reduced to 20, and the two latent variables LCI and CIR were combined into one variable, CC (consumer culture). The resulting model features two exogenous latent variables (Figure 2): the Cultural impact of rakija and the Level of consumer involvement. Preliminary analyses indicate that the R^2 value of .471 already surpasses the R^2 of .42 from the CB-SEM model. However, concerns have arisen regarding the variable Attitudes toward rakija. Namely, neither the path coefficient, that is, the direct effect of Attitudes toward rakija → Rakija purchase intentions $(\beta = .097, t = 1.834, p = .067)$, nor the specific indirect effects of Cultural impact of rakija → Attitudes toward rakija → Rakija purchase intentions $(\beta = .050, t = 1.779, p = .075)$ and Level of consumer involvement → Attitudes toward rakija → Rakija purchase intentions ($\beta = .020, t = 1.537, p = .124$) achieved statistical significance. In instances where neither the direct nor indirect effects are significant within a model, we encounter a scenario referred to as no-effect non-mediation (Zhao et al., 2010). Therefore, the latent variable Attitudes toward rakija was removed from the model as an endogenous variable.

Figure 2. Preliminary PLS-SEM model
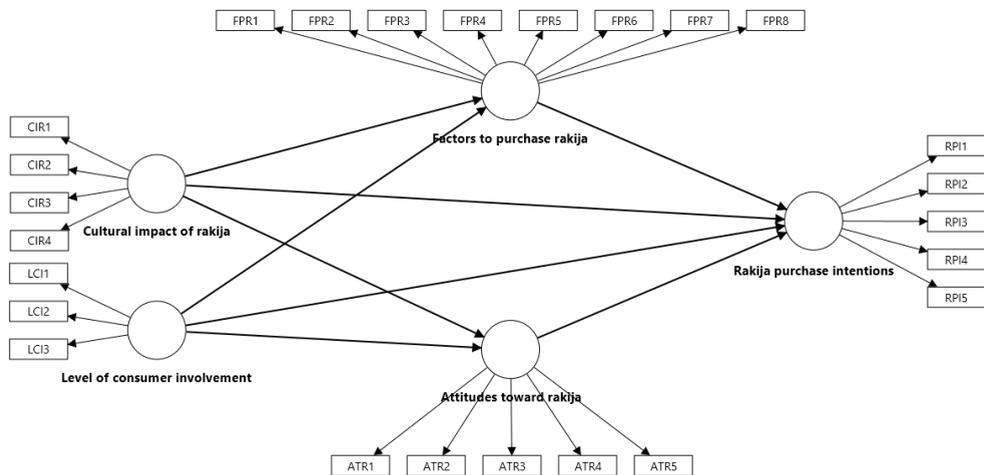
Source: Authors' calculations

Nevertheless, research indicates (Nagarjuna & Prasad, 2023; Xing & Jin, 2023) that cultural factors and values play a crucial role in shaping consumer attitudes towards products and brands; therefore, we believe that a model without this variable would be incomplete. Factors such as power distance, individualism, uncertainty avoidance, and masculinity have a positive effect on these attitudes, as they shape consumer values, beliefs, and preferences. Brand attitude frequently functions in models as a mediator or a connection between antecedents and purchase intention; however, a limited number of studies consider it as a moderator that either enhances or diminishes the relationship between predictors and purchase intention. The frameworks of consumer-brand relationships and emotional cognition provide foundational support for models in which attitudes interact with commitment, attachment, or product cues to influence

intentions (Gul et al., 2021). Consequently, research positions brand attitude as a mediator, moderator, or component within moderated mediation models, depending on the theoretical perspective and research inquiry. Razak et al. (2019) showed that brand attitude moderates the relationship between brand awareness and repurchase intention. Majeed et al. (2024) examined the moderating effects of consumer attitudes in the context of luxury brand purchases and the high retail prices of rakija (Adžić et al., 2024), which influence the fact that this drink is purchased mainly as a gift rather than for everyday consumption, certainly position this domestic alcoholic beverage as a luxury product. Consequently, the variable Attitudes toward rakija were examined in the model as a moderating variable.

The next modification of the model involved repositioning the Level of consumer involvement variable. It transitioned from an initial exogenous variable to a mediating endogenous variable in the model. Logic dictates (Hair et al., 2021) that the Cultural impact of rakija precedes the Level of consumer involvement, a perspective also supported by the existing literature. For instance, Gelbrich et al. (2023) highlighted the crucial role of cultural background in shaping consumer involvement in purchasing decisions by influencing values such as individualism, indulgence, and uncertainty avoidance. These values, in turn, affect how consumers search for, assess, and select products, thereby directing their purchasing behavior across various cultural settings. Figure 3 depicts a conclusive model suitable for further evaluation.

Figure 3. Final PLS-SEM model
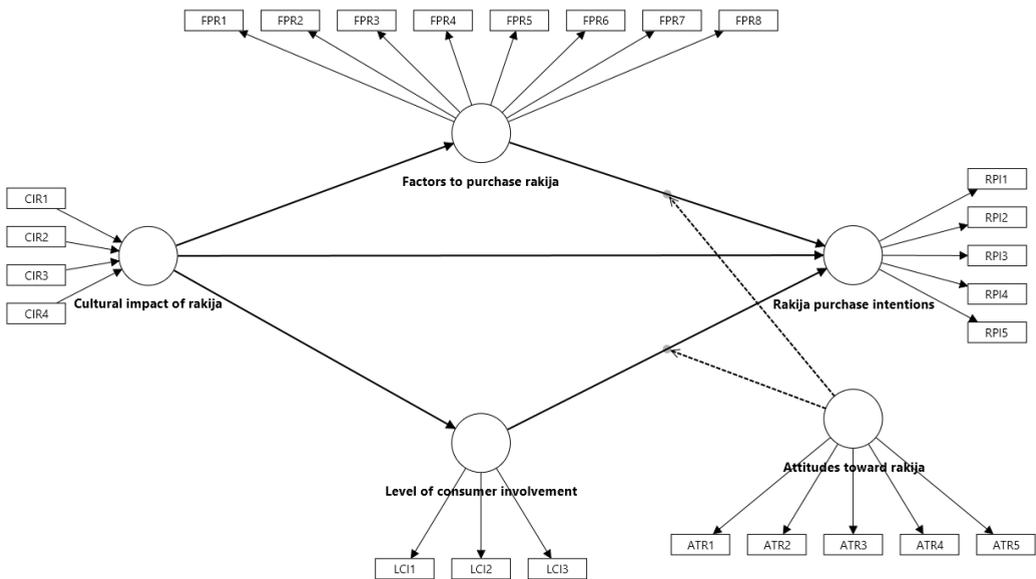
Source: Authors' calculations

Analysis of the measurement model

Given that data preparation (missing data and unengaged responses) and variable screening (skewness and kurtosis, common method bias, multicollinearity (VIF), and influentials) have already been positively verified in the CB-SEM model, we will not repeat these processes. Additionally, a demographic analysis of the respondents has already been conducted. We proceed with the multivariate analysis, beginning with the measurement model analysis. This analysis identifies the relationship between observed or measured variables and a latent variable in a specified study. It is essential to assess the reliability and validity of the measurement variables. The procedures for evaluating reflective and formative measurement models differ (Hair et al., 2021), and we began with the former model.

Figure 4. PLS-SEM algorithm
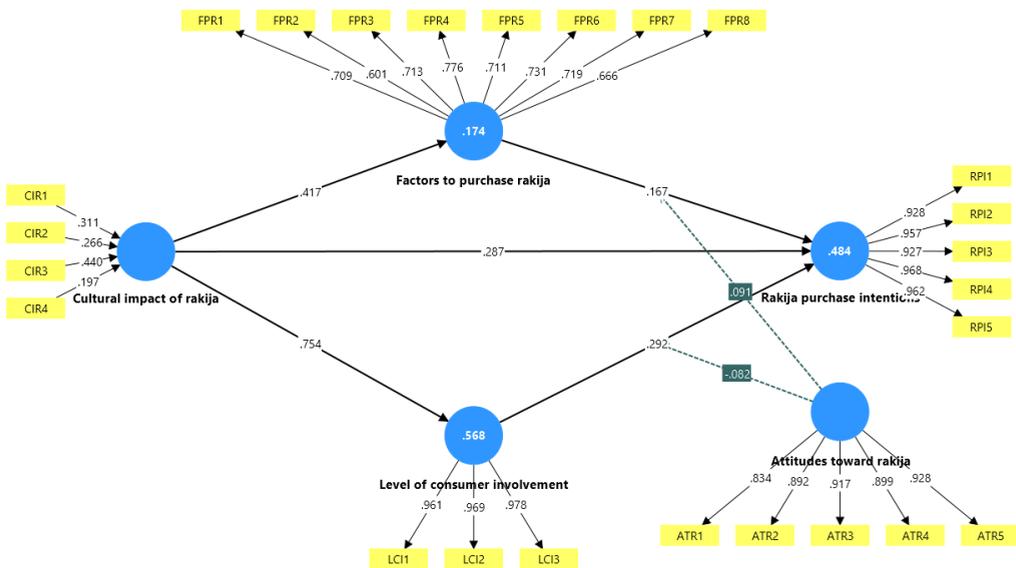
Source: Authors' calculations

The proposed *reflective measurement model* was evaluated using the PLS-SEM algorithm (Figure 4). Factor outer loading values above .708 and average variance extracted (AVE) values above .50 were used to determine convergent validity. Most of the factor loading values were greater than .708, which is considered acceptable (Table 1). Of the 21 factor loadings, two were below the strict threshold but still exceed the minimum limit of .40; thus, we will keep them. Three of the four Average Variance Extracted (AVE) values exceeded the threshold, while one was just below it (see Table 2). In fact, removing factor FPR2, which has a value of .601, would enhance the AVE score for the latent variable Factors to Purchase Rakija, bringing it above the threshold. However, this adjustment would result in a decrease of 0.1 percentage points in the R^2 value, which was not our intention. However, any adjustment would be contrary to research findings that close-fitting models may be inferior and causally

misspecified (Hayduk, 2014) and that improving model fit may come at the cost of theoretical integrity and a decrease in the replication of parameter values (Hermida, 2015). Therefore, we did not modify the originally established model. In conclusion, convergent reliability can be considered acceptable.

Table 1. Outer loadings matrix

	Attitudes toward rakija	Factors to purchase rakija	Level of consumer involvement	Rakija purchase intentions
ATR1	.834			
ATR2	.892			
ATR3	.917			
ATR4	.899			
ATR5	.928			
FPR1		.709		
FPR2		.601		
FPR3		.713		
FPR4		.776		
FPR5		.711		
FPR6		.731		
FPR7		.719		
FPR8		.666		
LCI1			.961	
LCI2			.969	
LCI3			.978	
RPI1				.928
RPI2				.957
RPI3				.927
RPI4				.968
RPI5				.962

Source: Authors' calculations

Cronbach's alpha values above .70 and composite reliability values above .70 were used to determine construct reliability. The construct reliability was confirmed as all Cronbach's alpha values for the latent variables, and all composite reliability values were green, that is, above the threshold (Table 2). Some researchers (e.g. Hair et al., 2019) suggested that a Cronbach's alpha above .9 may indicate potential concerns. However, high Cronbach's alpha values are not inherently problematic. A frequent issue in empirical research occurs when researchers include redundant items that do not provide new information, simply repeating the same aspect of the phenomenon, such as saying "I enjoy rakija" and "I really enjoy rakija." If the items capture different aspects of the constructs being assessed but still show a high correlation, it indicates a solid measurement model, as demonstrated in our study. A strong correlation among items that investigate various dimensions of constructs can signify a robust measurement model, particularly when evaluating convergent validity, which examines the connections between theoretically related constructs (Shenoy et al., 2021).

Table 2. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitudes toward rakija	.937	.939	.952	.800
Factors to purchase rakija	.863	.905	.887	.497
Level of consumer involvement	.968	.968	.979	.939
Rakija purchase intentions	.972	.972	.978	.900

Source: Authors' calculations

The primary criterion (Hair et al., 2012, p. 132) for discriminant validity assessment was the Heterotrait-Monotrait Ratio (HTMT). Discriminant validity was established when the HTMT value was below .90. In this study, all HTMT values were recorded as being under .90, as illustrated in Table 3. These findings indicate that all latent variables are unique, thereby confirming discriminant validity.

Table 3. Discriminant validity – Heterotrait-monotrait ratio (HTMT) matrix

	Attitudes toward rakija	Factors to purchase rakija	Level of consumer involvement	Rakija purchase intentions	Attitudes toward rakija x Level of consumer involvement	Attitudes toward rakija x Factors to purchase rakija
Attitudes toward rakija						
Factors to purchase rakija	.322					
Level of consumer involvement	.623	.404				
Rakija purchase intentions	.529	.424	.639			
Attitudes toward rakija x Level of consumer involvement	.207	.139	.017	.111		
Attitudes toward rakija x Factors to purchase rakija	.267	.133	.134	.087	.551	

Source: Authors' calculations

In this *the formative measurement model*, the key elements for model analysis are the bootstrapped outcomes for the outer weights. If we establish that the outer weights are relevant (positive and above zero) and significant, the model is considered positively tested (if not, see Hair et al. (2021, p. 152)). To obtain these results, we applied the bootstrapping procedure in PLS-SEM using 10,000 bootstrap samples and complete (slower) procedures. Streukens and Leroi-Werelds (2016) proposed that a minimum of 10,000 bootstrap samples should be used in PLS-SEM. According to the results presented in Table 4, we can conclude that the formative construct exhibits satisfactory quality levels.

**Table 4.** Outer weight bootstrapped results of the formative variable Cultural impact of rakija

	Original sample (O)	T statistics (|O/STDEV|)	P values	CI 2.5%	CI 97.5%
CIR1 -> Cultural impact of rakija	.311	4.581	.000	.177	.443
CIR2 -> Cultural impact of rakija	.266	3.708	.000	.128	.410
CIR3 -> Cultural impact of rakija	.440	6.553	.000	.306	.570
CIR4 -> Cultural impact of rakija	.197	3.690	.000	.096	.307

Source: Authors' calculations

Analysis of the structural model

The structural model was evaluated after confirming the overall validity of the measurement model. This analysis of the structural model was used to test the hypotheses (Hair et al., 2021). Nevertheless, the hypotheses were not established in this study. To obtain these results, we applied the bootstrapping procedure in PLS-SEM using 10,000 bootstrap samples and the most important (faster) procedures (Figure 5).

Figure 5. Bootstrapping output
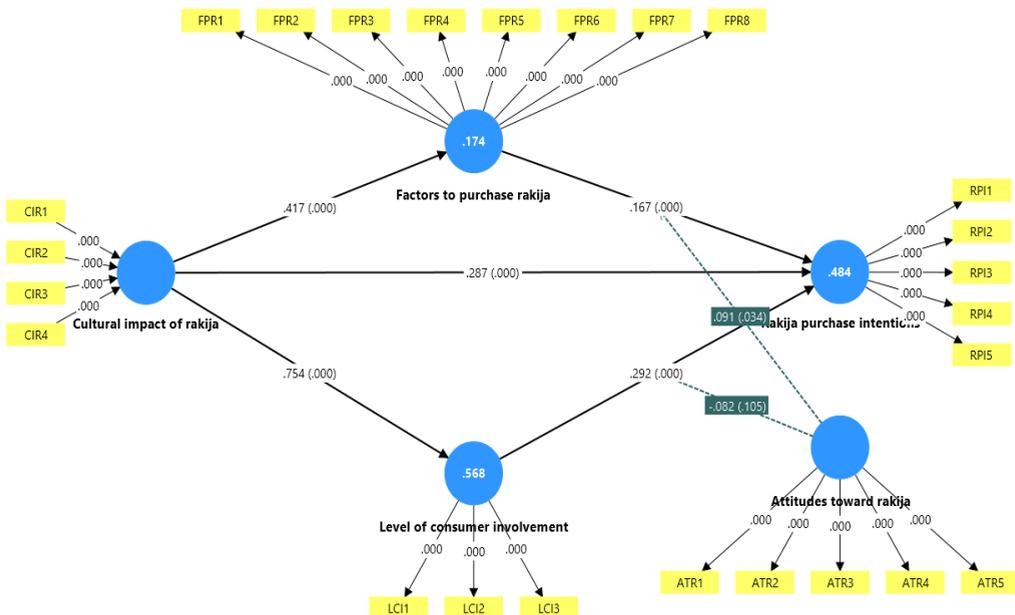
Source: Authors' calculations

Table 5 illustrates the results of the structural model (path coefficients, i.e., direct effects), including beta, t-statistics, and p-values. The results show that all five relationships are statistically significant.

Table 5. Path coefficients (direct effects)

	Original sample (O), i.e. β	T statistics (|O/STDEV|)	P values
Cultural impact of rakija -> Factors to purchase rakija	.417	9.642	.000
Cultural impact of rakija -> Level of consumer involvement	.754	33.326	.000
Cultural impact of rakija -> Rakija purchase intentions	.287	4.786	.000
Factors to purchase rakija -> Rakija purchase intentions	.167	3.687	.000
Level of consumer involvement -> Rakija purchase intentions	.292	4.491	.000

Source: Authors' calculations

Analysis of the explanatory power of the model and its effect size

Next, we shifted our focus to evaluating the explanatory power of the model. To accomplish this, we revisited the results generated by SmartPLS after executing of the PLS-SEM algorithm. The explanatory power of the structural model in PLS is determined by the coefficient of determination, commonly referred to as R^2. This value reflects the extent of the variance accounted for by all predictors of the dependent variable within the model (Hair et al., 2021). R^2 values of .75, .50, and .25 signify substantial, moderate, and weak explanatory powers, respectively. The study aimed to attain the maximum achievable R^2 for the final endogenous variable, Rakija purchase intentions. As illustrated in Table 6, the analysis shows that the model can explain approximately 48.4% of the variation in Rakija purchase intentions. Although the observed explanatory power of the Rakija purchase intentions variable is not substantial, the R^2 value of .484 from the PLS-SEM study is certainly larger than the R^2 value of .42 from the CB-SEM study.

Table 6. The explanatory power of the model R^2

	R-square	**Comment**
Factors to purchase rakija	.174	weak
Level of consumer involvement	.568	substantial
Rakija purchase intentions	.484	moderate

Source: Authors' calculations

Effect size f^2 aids in evaluating the extent to which an exogenous construct contributes to the R^2 value of the predictor latent variable (Hair et al., 2021). Table 12 shows the f^2 values for all combinations of endogenous constructs (represented by the columns) and the corresponding exogenous (i.e., predictor) constructs (represented by rows). The f^2 values of .02, .15, and .35 correspond to small, medium, and large effects, respectively. Effect size values below .02 suggest no measurable effects. In Table 7, substantial size

effects (medium and large) are displayed in green font, whereas small effect sizes are shown in black font. Insignificant effects are represented in red font, according to the thresholds established by Hair et al. (2012), which serve as the basis for the calculations performed by the SmartPLS software. However, Hair et al. (2021) recommend using values of .005, .01, and .025 for the moderator's f^2 effect size, which are classified as small, medium, and large, respectively, according to Kenny (2018). Accordingly, the effect size of Attitudes toward rakija x Factors to purchase rakija, which was statistically significant, was .014, indicating a medium effect size.

Table 7. The effect size f^2

	Cultural impact of rakija	Factors to purchase rakija	Level of consumer involvement	Rakija purchase intentions
Cultural impact of rakija		.210	1.314	.055
Factors to purchase rakija				.043
Level of consumer involvement				.066
Rakija purchase intentions				
Attitudes toward rakija x Level of consumer involvement				.009
Attitudes toward rakija x Factors to purchase rakija				.014

Source: Authors' calculations

For agricultural economics and agribusiness research, these results reinforce the relevance of PLS-SEM as a viable and methodologically sound alternative to CB-SEM.

Discussions and Conclusions

PLS-SEM exhibited a lower beta value for the total effects coefficient of the most significant path in the model, Cultural impact of rakija → Rakija purchase intentions, compared to CB-SEM, with values of .577 and .610, respectively. This observation, which indicates that the estimates from the PLS-SEM structural model are generally lower than those obtained from CB-SEM, was also noted by Reinartz et al. (2009). Conversely, as identified by Hair et al. (2024), the coefficients of determination, or R^2 values, for the two models diverge in the opposite manner. PLS-SEM recorded a higher R^2 value for the endogenous construct of Rakija purchase intentions than CB-SEM, with values of .484 compared to .420.

In the context of theory building, CB-SEM and AMOS are logical selections because they allow for the construction of a model and the adjustment of variables until an optimal fit is reached. Conversely, for theory testing, PLS-SEM and SmartPLS are appropriate options. Furthermore, when the objective is prediction, PLS-SEM is the preferred approach. In our case, the application of CB-SEM yielded a model that effectively analyzed the impact of culture on consumer purchasing behavior across all alcoholic beverages that hold cultural significance for consumers, extending beyond rakija. SEM-PLS identified a key factor within the model that influences consumer

purchasing behavior for the culturally specific product, Serbian rakija, highlighting an enhancement in the product's taste.

Undoubtedly, no modeling technique is without its flaws. PLS-SEM can generate formative latent variables that can be empirically validated using an advanced PLS-CTA model. In contrast, the CB-SEM does not accommodate formative variables. While CB-SEM can construct non-recursive models (with feedback loops) models, PLS-SEM is unable to do so. PLS-SEM evaluates differences among groups at the path level, whereas CB-SEM assesses differences at the group level, which is a benefit of CB-SEM.

CB-SEM is a common factor-based structural equation modeling method, with results derived from covariance and covariance matrices. In contrast, PLS-SEM employs a composite-based approach to structural equation modeling, generating results based on variance and real data. The estimation technique for CB-SEM utilizes maximum likelihood estimation, whereas PLS-SEM employs partial least squares estimation. Consequently, it is reasonable to expect that these methodologies may yield different outcomes, as evidenced by our model concerning the latent variable Attitude toward rakija.

SmartPLS also has a consistent PLS SEM (PLSc-SEM) algorithm. This algorithm can mimic CB-SEM (Hair et al., 2021). For those concerned about the discrepancies in the results between PLS-SEM and CB-SEM outputs, the two yield remarkably similar findings. Additionally, SmartPLS includes a Generalized Structured Component Analysis (GSCA) module. GSCA represents a composite-based SEM methodology similar to PLS (Hair et al., 2021). For those who prioritize this, GSCA enhances the overall model fit among composites; this does not have to be done in the SEM-PLS. Finally, SmartPLS is also capable of conducting CB-SEM analysis (Hair et al., 2025), positioning it as a versatile software that accommodates traditional, modern, and emerging SEM models (such as GSCA), establishing itself as an indispensable and comprehensive SEM software tool for researchers.

The primary contribution of this paper is methodological. The advantage of this study lies in its emphasis on the advantages and superiority of SmartPLS software and PLS-SEM over to AMOS and CB-SEM. Future research may extend this comparison to other agri-food products and cultural settings, as well as explore how methodological choices influence policy-relevant and managerial interpretations of consumer behavior models.

Conflict of interests

The authors declare no conflict of interest.

<div align="center">

References

</div>

1. Adžić, S. (2025). Exploring cultural influences on national alcoholic beverage purchases: A full latent variable structural equation model. *International Journal of Wine Business Research*, *37*(3), 445–475. https://doi.org/10.1108/IJWBR-05-2024-0029

2. Adžić, S., Pavlović, M., Milunović, M., Pavlović, Đ., Savić Tot, T., & Radanov, P. (2024). The impact of rakija cultural heritage and rakija marketing on the consumer purchasing decisions. *Economics of Agriculture*, *71*(3), 923–941. https://doi.org/10.59267/ekoPolj2403923A

3. Calvo-Porral, C., Rivaroli, S., & Orosa-Gonzalez, J. (2020). How consumer involvement influences beer flavour preferences. *International Journal of Wine Business Research*, *32*(4), 537–554. Emerald Insight. https://doi.org/10.1108/IJWBR-10-2019-0054

4. Gelbrich, K., Müller, S., & Westjohn, S. (2023). Cross-Cultural Consumer Behavior. In *Cross-Cultural Consumer Behavior*. Edward Elgar Publishing. https://www.elgaronline.com/monobook/book/9781803923192/9781803923192.xml

5. Gul, G. F., Gul, G. N., Gul, G. R., Zhenxing, G., Gul, G. W., & Nawaz, T. M. (2021). The Ties That Bind: Do Brand Attachment and Brand Passion Translate Into Consumer Purchase Intention? *Journal of Management and Business Administration. Central Europe*, *29*(1), 14–38.

6. Hair, J. F., Babin, B. J., Ringle, C. M., Sarstedt, M., & Becker, J.-M. (2025). Covariance-based structural equation modeling (CB-SEM): A SmartPLS 4 software tutorial. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-025-00414-6

7. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. SAGE Publications.

8. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2012). Partial Least Squares: The Better Approach to Structural Equation Modeling? *Long Range Planning, Analytical Approaches to Strategic Management: Partial Least Squares Modeling in Strategy Research*, *45*(5), 312–319. https://doi.org/10.1016/j.lrp.2012.09.011

9. 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

10. Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2024). *Advanced Issues in Partial Least Squares Structural Equation Modeling*. SAGE Publications, Incorporated.

11. Hayduk, L. (2014). Seeing Perfectly Fitting Factor Models That Are Causally Misspecified: Understanding That Close-Fitting Models Can Be Worse. *Educational and Psychological Measurement*, *74*(6), 905–926. https://doi.org/10.1177/0013164414527449

12. Hermida, R. (2015). The Problem of Allowing Correlated Errors in Structural Equation Modeling: Concerns and Considerations. *Computational Methods in Social Sciences*, *3*, 1–17.

13. Hwang, H., Sarstedt, M., Cheah, J. H., & Ringle, C. M. (2020). A concept analysis of methodological research on composite-based structural equation modeling: Bridging PLSPM and GSCA. *Behaviormetrika*, *47*(1), 219–241. https://doi.org/10.1007/s41237-019-00085-5

14. Kenny, D. A. (2018). *SEM: Moderation*. https://davidakenny.net/cm/moderation.htm

15. Kruger, M., & Viljoen, A. (2022). That old saying about wine and age: Identifying South African age-cohort preferences. *International Journal of Wine Business Research*, *34*(4), 495–522. Emerald Insight. https://doi.org/10.1108/IJWBR-06-2021-0033

16. Majeed, M. U., Aftab, H., Arslan, A., & Shakeel, Z. (2024). Determining online consumer's luxury purchase intention: The influence of antecedent factors and the moderating role of brand awareness, perceived risk, and web atmospherics. *PLOS ONE*, *19*(2), e0295514. https://doi.org/10.1371/journal.pone.0295514

17. Nagarjuna, B., & Prasad, K. R. (2023). Impact of Cultural Elements on Brand Preferences An Explorative Research. *European Journal of Business and Management*, *15*(10), 13–32.

18. Prendergast, G. P., Tsang, A. S. L., & Chan, C. N. W. (2010). The interactive influence of country of origin of brand and product involvement on purchase intention. *Journal of Consumer Marketing*, *27*(2), 180–188. https://doi.org/10.1108/07363761011027277

19. Razak, N., Themba, O. S., & Sjahruddin, H. (2019). Brand awareness as predictors of repurchase intention: Brand attitude as a moderator. *Advances in Social Sciences Research Journal*, *6*(2), 541–554. https://doi.org/10.14738/assrj.62.6264

20. Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing*, *26*(4), 332–344. https://doi.org/10.1016/j.ijresmar.2009.08.001

21. Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS* [Computer software]. Bönningstedt: SmartPLS. Retrieved from https://www.smartpls.com.

22. Shenoy, V., Aithal, P. S., & Raj, K. (2021). *Exploring Convergent Validity for Select Employability Skill Constructs* (SSRN Scholarly Paper No. 4079676). Social Science Research Network. https://doi.org/10.2139/ssrn.4079676

23. Spears, N., & Singh, S. (2004). Measuring Attitude Toward the Brand and Purchase Intentions. *Journal of Current Issues and Research in Advertising*, *26*, 53–66. https://doi.org/10.1080/10641734.2004.10505164

24. Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European Management Journal, European Management Research Using Partial Least Squares Structural Equation Modeling (PLS-SEM)*, *34*(6), 618–632. https://doi.org/10.1016/j.emj.2016.06.003

25. UNESCO. (2022). *UNESCO - Social practices and knowledge related to the preparation and use of the traditional plum spirit – šljivovica*. https://ich.unesco.org/en/RL/social-practices-and-knowledge-related-to-the-preparation-and-use-of-the-traditional-plum-spirit-ljivovica-01882

26. Wong, K. K.-K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, *24*(1), 1–32.

27. Xing, Y., & Jin, C.-H. (2023). The Impact of Cultural Values on Attitude Formation toward Cultural Products: Mediating Effects of Country Image. *Sustainability*, *15*(14), Article 14. https://doi.org/10.3390/su151411172

28. Yap, M. H. T. & Nan Chen. (2017). Understanding young chinese wine consumers through innovation diffusion theory. *Tourism & Hospitality Management*, *23*(1), 51–68. https://doi.org/10.20867/thm.23.1.3

29. Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257