
ADVANCED PLS-SEM APPLICATIONS IN MANAGEMENT RESEARCH: MODERATION, PREDICTION, AND MANAGERIAL INSIGHTS FROM THE RAKIJA CASE

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ABSTRACT

Recent methodological developments have expanded partial least squares structural equation modeling (PLS-SEM) beyond parameter estimation toward predictive and decision-oriented analytics. Building on a previously validated baseline PLS-SEM model of consumer purchasing behavior in the rakija market, this study demonstrates the analytical value of advanced PLS-SEM techniques using SmartPLS software. The analysis incorporates confirmatory tetrad analysis (CTA-PLS), bootstrapped mediation and moderation analysis, multigroup analysis (MGA), importance–performance map analysis (IPMA), and out-of-sample predictive assessment using PLSpredict. The results reveal conditional effects, segment-specific differences, and predictive patterns that remain undetected in baseline SEM applications. By systematically integrating multiple advanced procedures within a single empirical framework, the study illustrates how PLS-SEM can function as a comprehensive analytical toolkit for consumer and agribusiness research. The originality of the paper lies in demonstrating how advanced PLS-SEM techniques enhance interpretative depth, predictive relevance, and decision-oriented insights in culturally embedded markets.

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Introduction

Partial least squares structural equation modeling (PLS-SEM) has become an increasingly prominent analytical approach in consumer and agribusiness research, primarily due to its flexibility, robustness to non-normal data, and suitability for complex models with limited sample sizes. While earlier applications of PLS-SEM largely focused on parameter estimation and variance explanation, recent methodological developments have significantly expanded its analytical scope. Contemporary PLS-SEM (Ringle et al., 2024; Radovanović, 2025) is no longer limited to estimating structural relationships but has evolved into a comprehensive framework for predictive assessment, conditional effect analysis, and decision-oriented analytics.

Despite these advances, a substantial portion of empirical research continues to employ PLS-SEM in a relatively basic manner, generally limiting the analysis to the validation of measurement models and the estimation of direct structural relationships. As a result, important insights related to moderation, mediation, segment-specific effects, and predictive relevance often remain unexplored. This underutilization is particularly evident in studies examining culturally embedded products, where consumer behavior is shaped by complex interactions among attitudes, traditions, and social norms. In such contexts, advanced PLS-SEM techniques offer the potential to uncover nuanced behavioral mechanisms that extend beyond average effects. SmartPLS is gaining recognition due to its intuitive interface and sophisticated reporting capabilities, which improve accessibility for researchers (Wong, 2013).

Building on a previously validated baseline PLS-SEM model of consumer purchasing behavior in the rakija market, this study aims to demonstrate the added analytical value of advanced PLS-SEM procedures (Adžić et al., 2026). The baseline model, including construct operationalization and fundamental structural relationships, has been established and validated in prior research and serves here as a reference point for further methodological extension. Rakija, often referred to as rakia or schnapps, is a distilled alcoholic drink deeply rooted in Serbia's cultural and traditional practices (Adžić, 2023). A noteworthy acknowledgment of this beverage is the inclusion of Serbian plum rakija or šljivovica on the UNESCO World Heritage List.

SEM offers advantages over conventional multiple regression and other statistical methods (Keith, 2019). A key assumption for interpreting regression coefficients in a causal framework is that exogenous variables are measured without error, which is unlikely to be the case. Measurement errors present considerable challenges in research, and SEM effectively addresses these challenges. PLS has developed into a causal-predictive approach within SEM, focusing on explaining the variance in the model's dependent variables (Chin et al., 2020; Miljković & Arsić, 2025). The underlying causal-predictive rationale corresponds to what Gregor (2006) describes as theories that explain and predict. SEM is particularly suited for investigating models derived from explaining and predicting theories, and the causal-predictive features of PLS-SEM make it especially appealing for research aimed at producing actionable recommendations.

The key advantages of SmartPLS Partial Least Squares Structural Equation Modeling over AMOS Covariance-Based Structural Equation Modeling include its ability to handle smaller sample sizes, accommodate complex models, and focus on prediction rather than solely on model fit (Hair et al., 2012). PLS-SEM effectively handles high measurement errors, unbalanced datasets, and latent variables, making it ideal for analyzing relationships among latent constructs, particularly in small datasets. It combines the strengths of structural equation modeling and partial least squares, enhancing the flexibility of research studies (Ahmed et al., 2024). PLS-SEM focuses on prediction and can effectively accommodate non-normal data distribution (Usakli & Rasoolimanesh, 2023; Radomirović et al., 2025). PLS-SEM emphasizes the maximization of explained variance, rendering it particularly advantageous for prediction-oriented studies. In contrast, CB-SEM is primarily designed to validate theoretical frameworks. PLS-SEM is especially useful in exploratory research contexts because it permits the incorporation of formative indicators that enhance the explanation and prediction of constructs (Hair et al., 2014).

The primary objective of this paper is not to re-estimate or replicate the basic structural model, but rather to illustrate how advanced PLS-SEM techniques enrich model interpretation and practical usefulness. It demonstrates how advanced PLS-SEM techniques can reveal relationships and predictive patterns that remain hidden in basic model applications, particularly in markets characterized by cultural specificity and heterogeneous consumer segments. In doing so, the paper provides both researchers and practitioners with a structured illustration of how PLS-SEM can be fully leveraged to support theory development, managerial decision-making, and policy-relevant insights in agribusiness and consumer research.

Materials and methods

The researchers performed an extensive examination of scholarly journals and verified research scales pertaining to different types of alcoholic beverages (Adžić, 2025). This study analyzed five previously published research scales: the Cultural impact of rakija (CIR) (Yap & Nan Chen, 2017; Barović et al., 2025), the Level of consumer involvement (LCI) (Calvo-Porral et al., 2020), the Factors to purchase rakija (FPR) (Kruger & Viljoen, 2022), the Attitudes toward rakija (ATR) and the Rakija purchase intentions (RRI) (Spears & Singh, 2004). The data collected from the survey was assessed utilizing SmartPLS version 4.1.1.4.

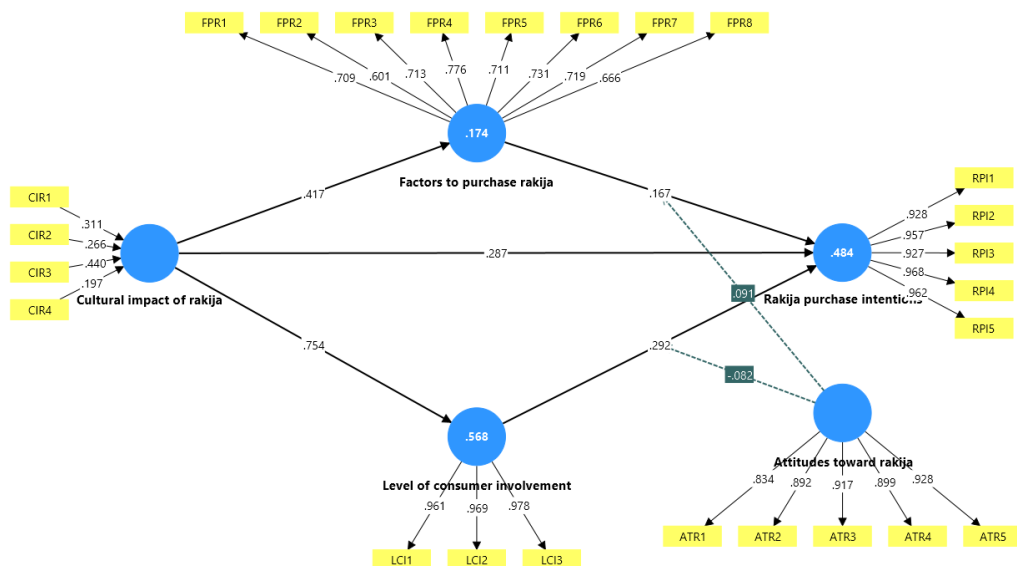
Results

Baseline PLS-SEM Model

The advanced analyses presented in this study build upon a previously validated baseline partial least squares structural equation model (PLS-SEM) of consumer purchasing behavior in the rakija market (Adžić et al., 2026). The baseline model specifies the core latent constructs and structural relationships grounded in consumer behavior theory

and cultural consumption literature. Construct operationalization, scale development, and data collection procedures are reported in detail in the preceding study and are therefore only briefly summarized here.

Figure 1. PLS-SEM model



Source: Adžić et al. (2026)

The baseline model was estimated using SmartPLS software and follows established PLS-SEM evaluation procedures (Figure 1). All constructs were modeled as reflective, and measurement model assessment confirmed internal consistency reliability, convergent validity, and discriminant validity based on composite reliability, average variance extracted (AVE), and heterotrait–monotrait (HTMT) ratios. The structural model demonstrated satisfactory explanatory power, with statistically significant path coefficients and acceptable levels of explained variance (R^2) for the endogenous constructs. Bootstrapping procedures were applied to assess the significance of direct and indirect effects.

Importantly, the purpose of the baseline model in the present study is not to replicate or re-evaluate its fundamental properties, but to serve as a methodological reference point for the application of advanced PLS-SEM techniques. By holding the core model structure constant, this study isolates the incremental analytical value provided by advanced procedures such as confirmatory tetrad analysis (CTA-PLS), moderation and mediation analysis, multigroup analysis (MGA), importance–performance map analysis (IPMA), and predictive assessment using PLSpredict. This approach ensures that any additional insights derived from the analysis can be attributed to methodological extension rather than changes in model specification.

Accordingly, the baseline PLS-SEM model functions as an analytical anchor that enables a systematic comparison between standard and advanced PLS-SEM applications. This

design strengthens the methodological contribution of the study by demonstrating how advanced techniques expand interpretative depth, uncover hidden heterogeneity, and enhance the practical relevance of SEM results in culturally specific agribusiness contexts.

Mediation analysis

Mediation occurs when a mediator construct intercedes between two directly related constructs, exogenous and endogenous constructs (Hair et al., 2021). Table 1 presents the results of the mediator analysis (indirect effects), including beta, t-statistics, and p-values. Both specific indirect effects of the LCI and FPR were statistically significant. In instances where the direct and indirect effects are both significant within a model and point in the same direction, we encounter a scenario referred to as complementary mediation (Zhao et al., 2010).

The mediators exhibit an indirect effect, resulting in lower beta values than direct effects, as their value comes from multiplying two decimal numbers whose values are below one. Thus, the established statistical significance is deemed more critical than the effect size, which is anticipated to be small. According to Hayes (2017), an effect size that approaches zero is often regarded as small, but the further the beta of a mediated variable strays from zero, the more substantial the perceived influence. The impact should always be evaluated against a reference point or a relevant factor.

Table 1. Results of the mediator analysis (indirect effects)

	β	t-statistics	p-values
SPECIFIC INDIRECT EFFECTS			
CRI -> LCI-> RPI	.220	4.512	.000
CRI -> FPR-> RPI	.070	3.585	.000
TOTAL INDIRECT EFFECTS			
CRI -> RPI	.290	6.407	.000

Source: Authors' calculations

Moderation effects

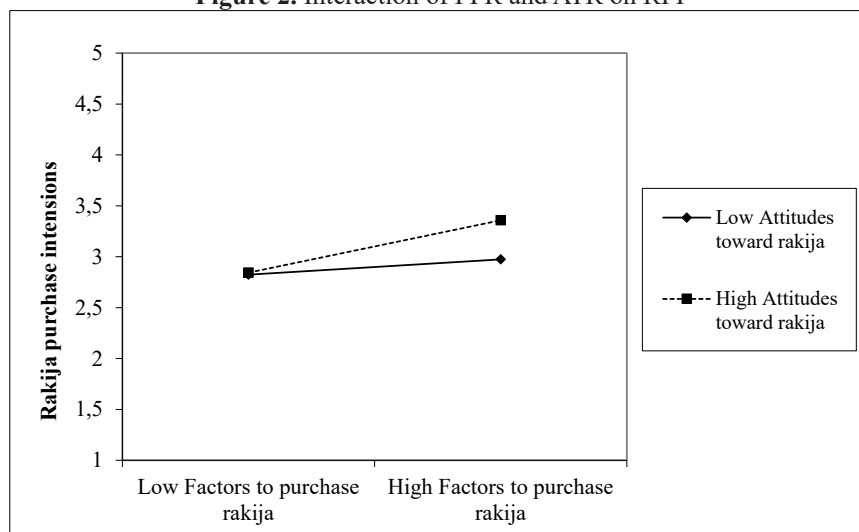
An additional variable in the analysis might change our comprehension of the direct relationships under investigation. When moderation is involved, the strength or direction of the relationship between two variables is affected by a third variable (the moderator). In other words, the connection between the two constructs shifts depending on the value of the moderator variable (Hair et al., 2021). Table 2 presents the moderating impact of ATR on the hypothesized relationships between FPR and RPI and the moderating impact of ATR on the hypothesized relationships between the LCI and RPI. The results showed that the interaction term of ATR x FPR had a significant positive effect on RPI, but ATR x LCI had an insignificant negative effect on RPI. This implies that the variable ATR only positively moderates the relationship between FPR and RPI .

Table 2. Results of the moderator analysis (interaction effects)

	β	t-statistics	p-values
ATR x FPR -> RPI	.091	2.125	.034
ATR x LCI-> RPI	-.082	1.619	.105

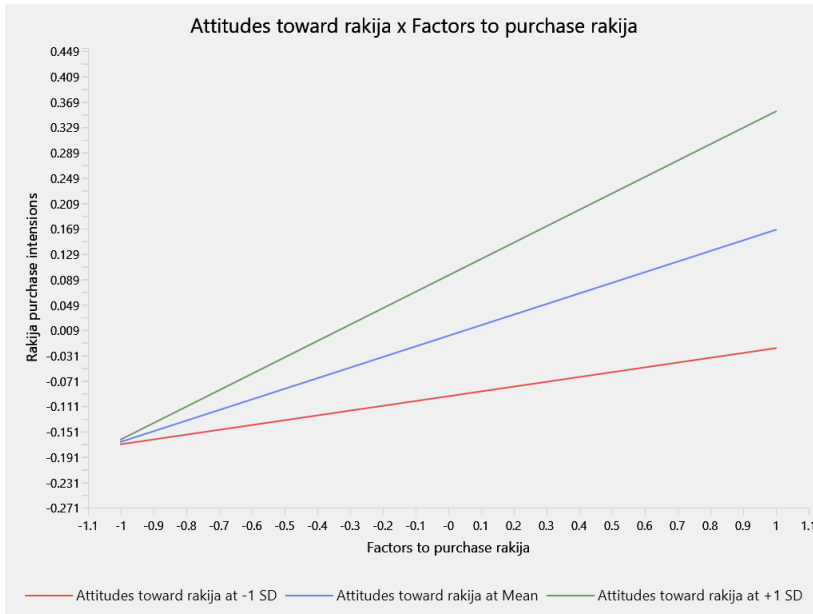
Source: Authors' calculations

In addition to understanding the elements of moderator analysis, interpreting the results is often challenging. Consequently, graphical representations of these results facilitate comprehension and the formulation of conclusions. A prevalent method for depicting the outcomes of moderation analysis is through the use of a slope plot, which provides the most comprehensible outcomes (Hasan, 2025). Figure 2 shows the slope analysis of the significant interaction effect. The graph illustrates that the effects of FPR on RPI will be stronger if ATR are high and conversely, weaker when ATR are low.

Figure 2. Interaction of FPR and ATR on RPI

Source: Authors' calculations

Since version 4, SmartPLS has provided the possibility of a graphical simple slope analysis of the moderator effect. The three lines shown in Figure 3 illustrate the relationship between the FPR (x-axis) and RPI (y-axis). The central line signifies the relationship at the mean level of the moderating variable, Attitudes toward rakija. The remaining two lines depict the relationship between the FPR and RPI at higher (i.e., the mean value of ATR plus one standard deviation) and lower (i.e., the mean value of ATR minus one standard deviation) levels of the moderating variable, Attitudes toward rakija. It is evident that the relationship between the FPR and RPI is positive across all three lines, as demonstrated by their upward slope. Therefore, the simple slope plot verified our earlier argument regarding the positive interaction effect: higher levels of ATR corresponded to a more robust relationship between the FPR and the RPI, whereas lower levels of ATR resulted in a weaker relationship between these factors.

Figure 3. Simple slope analysis – ATR x FPR

Source: Authors' calculations

Table 3 presents the results of the structural model (total effects), including beta, t-statistics, and p-values. The only difference in this table compared to the previous results is the heightened total effect relationship between the CRI and RPI. This increased value of .577 is the sum of the direct effect of .287 and the total indirect effect of .290. This relationship represents the longest connection in the model, linking the first exogenous variable to the last endogenous variable. Because the beta is greater than .5, the effect size is considered large; however, it is lower than the same beta of the CB-SEM model, which was .61 for this relationship.

Table 3. Total effects

	β	t-statistics	p-values
ATR x FPR -> RPI	.091	2.125	.034
ATR x LCI-> RPI	-.082	1.619	.105
CRI -> FPR	.417	9.642	.000
CRI -> LCI	.754	33.326	.000
CRI -> RPI	.577	11.766	.000
FPR -> RPI	.167	3.687	.000
LCI-> RPI	.292	4.491	.000

Source: Authors' calculations

Predictive assessment

The last step of the structural model evaluation process requires evaluating the model's predictive power using PLSpredict. For a PLS path model to be effective in managerial

decision-making, it is essential that it yields generalizable results. Achieving generalizable results requires an evaluation of whether the findings are applicable to the data utilized in the model estimation and to other datasets that were not part of the estimation process. Consequently, researchers must evaluate the out-of-sample predictive capability of their model, or in a few words, its predictive power (Hair et al., 2021).

Our investigation centers on the key target construct of the model, which is Rakija purchasing intentions (RPI), and we utilize the root mean square error (RMSE) as the standard measure for assessing the prediction error associated with the indicators of this construct (Table 4). Initially, we analyzed five RPI Q²predict values. The results indicate that each of the five Q²predict values (RPI1, RPI2, RPIS3, RPIS4, and RPI5) exceeded zero. A positive Q²predict value indicates that the prediction error of the PLS path model is less than that of the most basic benchmark (i.e., the indicator means derived from the analysis sample), indicating that the PLS model surpasses the naïve benchmark.

The next analysis required a comparison of the RMSE values generated by the PLS-SEM analysis with those produced by the naïve linear regression model (LM) benchmark. Upon comparing the RMSE values, we observed that PLS-SEM analysis yielded lower prediction errors (i.e., smaller RMSE values) than LM across all five RPI indicators. Given that all indicators in the PLS-SEM analysis exhibited lower RMSE values than the naïve LM benchmark, it can be concluded that the model possessed substantial predictive power.

Table 4. PLSpredict MV summary

	Q ² predict
FPR1	.203
FPR2	.005
FPR3	-.005
FPR4	.128
FPR5	.017
FPR6	.019
FPR7	.037
FPR8	.073
LCI1	.504
LCI2	.550
LCI3	.526
RPI1	.353
RPI2	.366
RPI3	.377
RPI4	.338
RPI5	.329

Source: Authors' calculations

CTA-PLS results

Based on the data and model we established, we can apply three advanced models. The first, confirmatory tetrad analysis, was conducted to empirically evaluate whether the data aligned with formative or reflective measurement model specifications. To successfully address the challenge of precisely defining the measurement model, we performed an advanced SmartPLS analysis, particularly the confirmatory tetrad analysis for PLS-SEM (CTA-PLS). This analysis empirically assesses whether the data conforms to the formative or reflective measurement model specifications (Hair et al., 2024). A significant test statistic indicates that the measurement model is formative in nature. According to Lowry and Gaskin (2014), the threshold for acceptable model fit is 80%. A threshold of 80% indicates that if 80% of the measurement variables exhibit significant p-values, the variable is formative. CTA-PLS identified only one of the four latent variables (Consumer involvement level was excluded because it consisted of fewer than four measurement variables) as formative. All measurement items related to the variable CIR were significant (Table 5). Thus, we adjusted the direction of this variable's arrows in PLS-SEM to align them with the formative measurement model for the specified variable. The formative model of culture aligns with Schein's (2010) cultural model, where artifacts represent the most visible level of culture. Additionally, this logic (Hair et al., 2021) supports the assertion that CIR measurement variables build the concept of the cultural impact of rakija.

Table 5. Statistically significant results of the confirmatory tetrad analysis

CRI	Original sample (O)	T-statistics	p-values	CI low	CI up
1: CIR1,CIR2,CIR3,CIR4	.904	2.740	.006	.371	1.456
2: CIR1,CIR2,CIR4,CIR3	1.262	4.004	.000	.755	1.791

Source: Authors' calculations

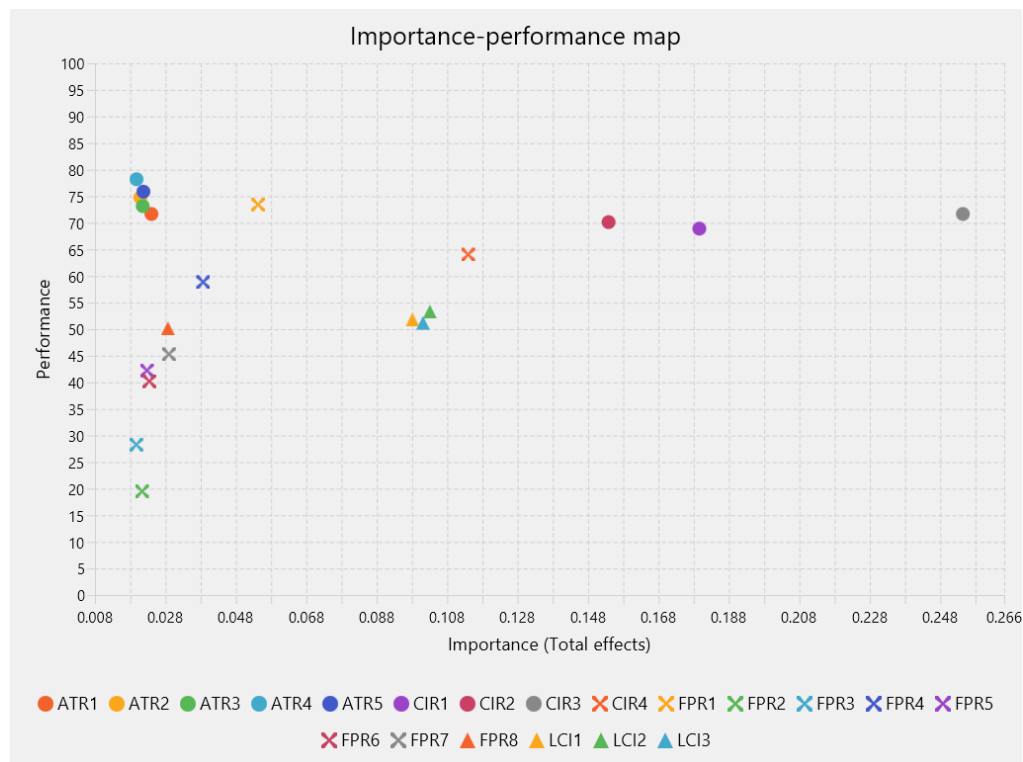
IPMA results

In this section, we present the importance-performance map analysis, a quantitative analysis for qualitative decision-making, and the multigroup analysis to examine the differences between group-specific path coefficients.

The analysis known as Importance-performance map analysis (IPMA), also known as priority map analysis, enhances the conventional results obtained from PLS-SEM by locating specific areas that require improvement. This provides a solid empirical basis for a more informed discussion on enhancing the performance of the key target constructs. Specifically, the IPMA contrasts the total effects, which reflect the importance of predecessor constructs in predicting a particular target construct, against their average latent variable scores, which denote their performance. The rationale behind this approach is to identify predecessor constructs that exhibit relatively high importance in predicting the target construct (i.e., those with a strong total effect) while simultaneously demonstrating relatively low performance (i.e., low average latent variable scores), thereby allowing targeted improvements to be made (Hair et al., 2021).

Figure 4 illustrates the SmartPLS IPMA model derived from our empirical data analysis. The indicators located in the lower right section of the IPMA model exhibit a high level of importance for the target construct, yet demonstrate low performance, and vice versa. These findings indicate that CIR3 warrants the utmost priority for enhancement. The priority indicator CIR3 is that Rakija has a pleasant taste. The unpleasant taste of rakija has been identified as a problem for some distillery producers (Adžić, 2023). IPMA analysis showed that taste is the most important factor in consumers' decisions regarding which rakija to purchase.

Figure 4. IPMA: RPI indicators



Source: Authors' calculations

MGA results

The multigroup analysis in SmartPLS evaluates the statistical significance of the differences among the group-specific path coefficients. Path coefficients derived from various samples typically exhibit numerical differences; however, the critical question is whether these differences are statistically significant. Multigroup analysis provides researchers with the necessary tools to address this question. Various approaches are available for conducting multigroup analyses in SmartPLS (Hair et al., 2024).

Table 6. Bootstrap MGA for the rakija and wine group

	Difference (Prefer rakija to wine - Prefer wine to rakija)	2-tailed (Prefer rakija to wine vs Prefer wine to rakija) p value
CRI -> FPR	.040	.616
CRI -> LCI	.005	.918
CRI -> RPI	-.070	.553
FPR -> RPI	.025	.795
LCI-> RPI	-.121	.351

Source: Authors' calculations

We implemented the bootstrap multigroup analysis (MGA) as recommended by Hasan (2025). The initial step involved generating groups within the data files. According to the CB-SEM analysis conducted by Adžić (2025), two independent multigroup models were developed. One group evaluated the model for respondents who consume rakija but prefer wine, while the other group assessed those who consume and prefer beer in comparison to those who consume and prefer rakija. The first multigroup results (Table 6) indicate that all differences observed between the rakija and wine groups were insignificant. The same result was obtained for the CB-SEM analysis.

The second multigroup results (Table 7) indicated that only one difference between the rakija and beer groups was statistically significant at the .05 level. The path coefficient for those who prefer rakija over beer is .109 ($p = .037$) higher than that for those who prefer beer over rakija, indicating that culture is an important factor influencing rakija consumers' purchasing behavior. This suggests that these consumers tend to purchase alcoholic beverages that are deeply embedded in the cultural and traditional practices of Serbia, in contrast to beer consumers, for whom culture and the origin of beer do not have a significant influence. While a comparable outcome was observed in the CB-SEM analysis, AMOS determined the difference at the overall group level rather than among the path coefficients specific to each group, which we recognize as a significant benefit of AMOS.

Table 7. Bootstrap MGA for the rakija and beer group

	Difference (Prefer rakija to beer - Prefer beer to rakija)	2-tailed (Prefer rakija to beer vs Prefer beer to rakija) p value
CRI -> FPR	-.013	.858
CRI -> LCI	.109	.037
CRI -> RPI	-.054	.618
FPR -> RPI	-.049	.624
LCI-> RPI	.031	.821

Source: Authors' calculations

Discussions and Conclusions

The results of this study demonstrate that advanced PLS-SEM techniques substantially enhance the analytical depth and practical relevance of consumer behavior models beyond what can be achieved through baseline SEM applications. By applying multiple advanced procedures within a single empirical framework, the analysis reveals conditional relationships, segment-specific effects, and predictive patterns that remain hidden in standard structural model estimation.

SmartPLS software is known for its practicality. It is designed to be user-friendly and does not necessitate the use of SPSS, unlike AMOS; only applications such as Excel are required to create databases. Additionally, descriptive statistics can be performed using SmartPLS. Its intuitive nature is evidenced by the significant or above-threshold results presented in tables with green fonts. Conversely, the results shown in red indicate problems. This color coding also aids graphical modeling by highlighting the variables that lack connections. Transitioning from AMOS to SmartPLS (Ringle et al., 2024) in its fourth version is not only a robust alternative to AMOS, as Wong (2013) suggests, but also a software with the user-friendly interface.

For researchers engaged in regression analysis, PLS-SEM presents a familiar framework that allows for swift comprehension and acceptance of SmartPLS. An analysis encompassing both latent and observed variables will yield a more comprehensive understanding. This will provide multiple perspectives and reveal a broader array of options for addressing theoretical and practical problems. Notably, the advanced method known as IPMA facilitates quantitative analysis for qualitative decision-making, thereby augmenting the traditional outcomes derived from PLS-SEM by pinpointing specific areas in need of enhancement. The IPMA serves as a genuine roadmap for managers to follow. Moreover, considering the benefits of PLS-SEM (Ahmed et al., 2024; Hair et al., 2012; Usakli & Rasoolimanesh, 2023), such as higher statistical power, the ability to handle smaller sample sizes, adaptation to complex models, efficient handling of high measurement errors and unbalanced datasets, efficient adaptation to non-normal data distributions, and focus on prediction rather than model fitting, we favor analyses grounded in PLS-SEM.

This study demonstrates the added value of advanced PLS-SEM techniques in consumer and agribusiness research using the rakija market as an empirical context. By extending a previously validated baseline model through moderation, mediation, multigroup, importance–performance, and predictive analyses, the paper illustrates how advanced PLS-SEM procedures uncover insights that remain inaccessible through basic SEM applications.

The contribution of this paper is both methodological and practical. Methodologically, it provides a structured illustration of how advanced PLS-SEM techniques can be systematically integrated within a single empirical study. Practically, it shows how these techniques enhance decision-oriented interpretation and predictive relevance in culturally specific markets.

Conflict of interests

The authors declare no conflict of interest.

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