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# Machine Learning Identification of Cultural Value Systems Using Collectivism, Power Distance, and Uncertainty Avoidance

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A B S T R A C T

**Objective:** The present study aimed to identify and model latent cultural value system profiles using machine learning techniques based on collectivism, power distance, and uncertainty avoidance.

**Methods and Materials:** This study employed a cross-sectional, descriptive–analytical design with a predictive modeling approach. The sample consisted of 512 adult participants from Canada selected through stratified random sampling to ensure demographic and cultural diversity. Data were collected using standardized instruments measuring collectivism, power distance, and uncertainty avoidance, all of which demonstrated established validity and reliability in prior research. After data preprocessing, including normalization and handling of missing values, both supervised and unsupervised machine learning techniques were applied. Classification models included support vector machines, random forest, gradient boosting, and logistic regression, while k-means clustering was used to identify latent cultural profiles. Model evaluation was conducted using stratified k-fold cross-validation, with performance metrics including accuracy, precision, recall, F1-score, and AUC-ROC. Feature importance and interpretability were assessed using SHAP analysis.

**Findings:** The results indicated significant positive associations among collectivism, power distance, and uncertainty avoidance ($p < 0.01$). Among classification models, gradient boosting demonstrated the highest predictive performance (AUC-ROC = 0.927), followed by random forest (AUC-ROC = 0.912), indicating strong model discrimination. Logistic regression showed comparatively lower performance, suggesting the presence of nonlinear relationships among variables. Clustering analysis identified three distinct cultural profiles characterized by low, moderate, and high levels of the examined dimensions. Feature importance analysis revealed that power distance was the strongest predictor of cultural profile classification, followed by uncertainty avoidance and collectivism.

**Conclusion:** The study underscores the importance of power distance and uncertainty avoidance in shaping cultural profiles and supports the utility of advanced computational methods in cultural research.

***Keywords:*** *Cultural Value Systems, Collectivism, Power Distance, Uncertainty Avoidance, Cultural Psychology*

## 1 Introduction

Understanding cultural value systems has long been a central concern in the social sciences, particularly in disciplines such as psychology, sociology, organizational behavior, and international management. Cultural values function as deeply embedded cognitive schemas that shape individuals' perceptions, decision-making processes, and behavioral patterns across a wide range of social contexts. Among the most influential frameworks for conceptualizing cultural values is the dimensional approach introduced by Hofstede, which identifies key constructs such as collectivism, power distance, and uncertainty avoidance as fundamental axes of cultural variation. These dimensions have been widely applied to explain cross-national differences in organizational practices, communication styles, consumer behavior, and institutional structures (Moradi, 2024; Offiah et al., 2025). Despite the extensive application of these constructs, traditional analytical approaches have often struggled to capture the complex, nonlinear, and interactive nature of cultural value systems, thereby limiting the depth and precision of empirical insights.

Collectivism represents the degree to which individuals prioritize group cohesion, interdependence, and shared goals over personal autonomy and individual achievement. In collectivistic contexts, social identity is closely tied to group membership, and behaviors are guided by norms that emphasize harmony, cooperation, and loyalty. Empirical research has consistently demonstrated that collectivism influences a wide range of outcomes, including consumer preferences, organizational commitment, and social behaviors (Mohamed, 2024; Riaz et al., 2023). Power distance, by contrast, reflects the extent to which individuals accept hierarchical structures and unequal distributions of power within society. High power distance cultures tend to legitimize authority and centralized decision-making, whereas low power distance cultures emphasize egalitarianism and participatory governance. This dimension has been shown to affect leadership styles, institutional trust, and workplace dynamics (Polatcan et al., 2025; Tong, 2024). Uncertainty avoidance captures individuals' tolerance for ambiguity and their preference for structured, predictable environments. Cultures characterized by high uncertainty avoidance tend to rely on formal rules, procedures, and risk-averse behaviors, whereas low uncertainty avoidance cultures exhibit greater openness to change and innovation (Chen & Biswas, 2022; Shen et al., 2024).

The significance of these cultural dimensions extends beyond individual-level attitudes to broader societal and organizational outcomes. For instance, cultural values have been linked to economic growth trajectories, innovation capacity, and institutional effectiveness (Geng & Tan, 2021; Lee et al., 2022). In organizational contexts, cultural orientations shape leadership expectations, communication patterns, and employee performance, thereby influencing overall organizational effectiveness (Asiedu et al., 2023; Venkatesh et al., 2022). Moreover, cultural dimensions play a critical role in shaping responses to global challenges, such as public health crises, where variations in uncertainty avoidance and collectivism have been associated with differences in compliance behaviors and policy effectiveness (Chen & Biswas, 2022). These findings underscore the multifaceted and pervasive influence of cultural values across domains, highlighting the need for more sophisticated analytical approaches capable of capturing their complexity.

In recent years, advances in machine learning have opened new avenues for the study of cultural value systems. Unlike traditional statistical methods, which often rely on linear assumptions and predefined model structures, machine learning techniques are capable of identifying complex patterns, nonlinear relationships, and high-order interactions within large datasets. This makes them particularly well-suited for modeling cultural phenomena, which are inherently multidimensional and context-dependent. For example, machine learning approaches have been used to predict consumer preferences, behavioral outcomes, and social attitudes based on cultural variables, demonstrating superior predictive accuracy compared to conventional methods (Ma et al., 2024; Wang et al., 2021). Furthermore, clustering algorithms enable the identification of latent cultural profiles within populations, revealing patterns that may not be apparent through traditional analytical techniques.

The integration of cultural theory with machine learning methods represents a promising but still underdeveloped area of research. While existing studies have applied machine learning to cultural data, many have focused on isolated outcomes rather than the holistic identification of cultural value systems. Additionally, there remains a lack of research that explicitly examines the combined effects of collectivism, power distance, and uncertainty avoidance within a unified modeling framework. Addressing this gap is particularly important given that these dimensions are not independent but interact dynamically to shape individuals'



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cognitive and behavioral orientations. For instance, the interplay between collectivism and power distance may influence negotiation styles and communication strategies in cross-cultural interactions (Li & Liu, 2024), while the interaction between uncertainty avoidance and collectivism may affect risk perception and decision-making under uncertainty (Dhingra et al., 2024).

Another important consideration is the role of cultural values in shaping communication, media engagement, and digital behavior. In the era of globalization and digital transformation, individuals increasingly interact across cultural boundaries, making it essential to understand how cultural value systems influence online behavior and communication patterns. Research has shown that cultural differences significantly affect social media usage, online rating behaviors, and digital communication strategies (Wang, 2025; Xu & Duan, 2023). Similarly, cultural values influence how organizations design global public relations campaigns and engage with diverse audiences (Mandela, 2024). These insights highlight the relevance of cultural value systems in contemporary digital environments and underscore the need for analytical approaches that can accommodate the complexity of these interactions.

Cultural values also play a critical role in shaping responses to innovation, technology adoption, and consumer behavior. For example, individuals from different cultural backgrounds exhibit varying levels of openness to new technologies, risk tolerance, and preference for innovation, which in turn influence market dynamics and product adoption patterns (Ma et al., 2024; Yeganeh, 2023). In educational and technological contexts, cultural dimensions have been shown to affect user interface preferences, learning styles, and engagement with digital platforms (Tandra & Rofil, 2023). These findings further emphasize the importance of understanding cultural value systems as dynamic and context-sensitive constructs that influence behavior across multiple domains.

Despite the growing body of research on cultural values, several methodological limitations persist. Many studies rely on self-report measures and linear statistical techniques, which may not fully capture the complexity of cultural phenomena. Additionally, cross-cultural comparisons often assume homogeneity within national populations, overlooking the existence of subcultural variations and hybrid cultural identities. Machine learning offers a powerful alternative by enabling the identification of latent patterns and heterogeneity within datasets, thereby providing a more nuanced understanding of cultural value systems. Clustering techniques, in particular, can reveal distinct cultural profiles within a single population, challenging traditional assumptions about cultural uniformity (Bonjeer & Voňková, 2023; Zapata et al., 2022).

Furthermore, the application of machine learning to cultural research aligns with broader trends toward data-driven decision-making and computational social science. By leveraging large datasets and advanced analytical techniques, researchers can generate more accurate and generalizable insights into the determinants of behavior. This approach is particularly relevant in the context of globalized societies, where cultural interactions are increasingly complex and multifaceted. Studies examining intercultural communication, tourism behavior, and corporate reputation have highlighted the importance of cultural values in shaping stakeholder perceptions and interactions (Casais & Cardoso, 2023; Pérez-Cornejo et al., 2021). Similarly, research on cross-cultural conflict and organizational dynamics underscores the role of cultural differences in shaping interpersonal and institutional outcomes (Santi, 2020; Shamsabadi et al., 2020).

In addition to these considerations, cultural values are deeply intertwined with social norms, health behaviors, and well-being outcomes. For instance, cultural factors have been linked to variations in health behaviors, stress responses, and even the prevalence of certain medical conditions across populations (Muchsini & Siswandari, 2020; Rajkumar, 2023). These findings highlight the broader societal implications of cultural value systems and reinforce the importance of developing robust analytical frameworks for their study. Moreover, cultural values influence ethical norms, privacy concerns, and information-sharing behaviors, particularly in digital environments where cultural differences can have significant implications for policy and practice (Paul et al., 2021; Wan Abdul Rahim Wan Mohd et al., 2020).

Taken together, the existing literature underscores the centrality of collectivism, power distance, and uncertainty avoidance in shaping human behavior across diverse contexts. However, there remains a need for integrative approaches that combine theoretical rigor with methodological innovation. By leveraging machine learning techniques, researchers can move beyond traditional analytical constraints and develop more comprehensive models of cultural value systems. Such approaches not only enhance predictive accuracy but also provide deeper insights into the underlying mechanisms that drive cultural variation.



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Therefore, the present study aims to identify and model cultural value systems using machine learning techniques based on collectivism, power distance, and uncertainty avoidance within a diverse population context.

## 2 Methods and Materials

### *2.1 Study Design and Participants*

This study employed a cross-sectional, descriptive–analytical design with a predictive modeling approach grounded in supervised and unsupervised machine learning techniques. The target population consisted of adult residents of Canada across diverse cultural, ethnic, and socioeconomic backgrounds to ensure variability in cultural value orientations. A total of 512 participants were recruited using stratified random sampling procedures, ensuring proportional representation across provinces, gender, age groups, and educational levels. Inclusion criteria required participants to be at least 18 years old, fluent in English or French, and residents of Canada for a minimum of five years to ensure adequate exposure to societal cultural norms. Data collection was conducted through an online survey platform, and informed consent was obtained electronically prior to participation. The sample size was determined based on both statistical power considerations for multivariate modeling and the requirements of machine learning algorithms to achieve stable generalization performance.

### *2.2 Measures*

Cultural value systems were assessed using standardized psychometric instruments operationalizing collectivism, power distance, and uncertainty avoidance as core constructs. Collectivism was measured using the Individualism–Collectivism Scale originally developed by Triandis and colleagues, which consists of 16 items assessing the extent to which individuals prioritize group goals over personal goals, value interdependence, and maintain strong in-group affiliations. Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree, with higher scores indicating stronger collectivistic orientation. Power distance was assessed using the Power Distance Scale adapted from Hofstede's cultural dimensions framework, comprising 10 items that evaluate individuals' acceptance of hierarchical structures, authority, and unequal power distribution within social systems. Uncertainty avoidance was measured using the Uncertainty Avoidance Index Scale, consisting of 12 items designed to capture tolerance for ambiguity, preference for structured situations, and discomfort with uncertain or unpredictable environments. All instruments have demonstrated robust psychometric properties in prior cross-cultural research, including high internal consistency coefficients (Cronbach's alpha typically exceeding 0.80) and established construct validity through confirmatory factor analysis. Demographic information, including age, gender, education level, income, and cultural background, was also collected to enable additional exploratory analyses and control for potential confounding variables.

### *2.3 Data Analysis*

Data analysis was conducted using a combination of traditional statistical methods and advanced machine learning techniques. Initial preprocessing steps included data cleaning, handling of missing values באמצעות multiple imputation, normalization of continuous variables, and encoding of categorical variables where necessary. Exploratory data analysis was performed to assess distributional properties and detect potential outliers. Subsequently, feature selection techniques, including recursive feature elimination and mutual information criteria, were applied to identify the most informative predictors of cultural value system profiles. For the machine learning phase, multiple algorithms were implemented, including support vector machines, random forest classifiers, gradient boosting machines, and k-means clustering for unsupervised pattern detection. Model performance was evaluated using cross-validation procedures, specifically stratified k-fold cross-validation, to ensure generalizability and prevent overfitting. Performance metrics included accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) for classification models, as well as silhouette scores and Davies–Bouldin indices for clustering solutions. Hyperparameter tuning was conducted באמצעות grid search optimization to identify the optimal configuration for each model. Additionally, model interpretability techniques such as SHAP (Shapley Additive Explanations) values were employed to quantify the contribution of each cultural variable to the prediction outcomes, thereby enhancing the theoretical interpretability of the machine learning results within the cultural psychology framework.



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## 3 Findings and Results

The final sample consisted of 512 participants residing in Canada, with a balanced gender distribution (51.17% female, 47.85% male, and 0.98% identifying as non-binary or other). The mean age of participants was 34.62 years (SD = 9.48), ranging from 18 to 65 years. In terms of educational attainment, 28.91% held a high school diploma or equivalent, 41.02% had completed undergraduate studies, and 30.07% possessed graduate-level qualifications. Regarding cultural background, participants represented a diverse array of ethnic identities, with 46.68% identifying as European Canadian, 22.46% as Asian Canadian, 14.84% as Middle Eastern or North African, 9.57% as African or Caribbean, and 6.45% as other or mixed backgrounds. The average length of residence in Canada was 16.73 years (SD = 8.21), indicating substantial exposure to Canadian sociocultural contexts. These demographic characteristics ensured sufficient heterogeneity for robust machine learning modeling of cultural value systems.

**Table 1**

*Descriptive Statistics and Correlations Among Core Study Variables*

| Variable | Mean | SD | 1 | 2 | 3 |
|---|---|---|---|---|---|
| 1. Collectivism | 3.68 | 0.74 | — | | |
| 2. Power Distance | 3.21 | 0.69 | 0.42** | — | |
| 3. Uncertainty Avoidance | 3.47 | 0.72 | 0.36** | 0.48** | — |

Table 1 presents the descriptive statistics and Pearson correlation coefficients for the primary variables of interest. The mean scores indicate moderate levels of collectivism, power distance, and uncertainty avoidance within the sample, suggesting variability in cultural orientations even within a single national context. The correlation matrix reveals statistically significant positive associations among all three variables. Collectivism demonstrated a moderate positive correlation with power distance ($r = 0.42$, $p < 0.01$), indicating that individuals who prioritize group cohesion also tend to exhibit greater acceptance of hierarchical structures. Similarly, collectivism was positively associated with uncertainty avoidance ($r = 0.36$, $p < 0.01$), suggesting that group-oriented individuals may prefer structured and predictable environments. The strongest correlation was observed between power distance and uncertainty avoidance ($r = 0.48$, $p < 0.01$), highlighting a meaningful convergence between hierarchical acceptance and intolerance of ambiguity. These interrelationships provide a foundational basis for subsequent machine learning modeling, indicating that while the constructs are distinct, they are meaningfully interconnected.

**Table 2**

*Machine Learning Classification Performance Across Models*

| Model | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| Support Vector Machine | 0.842 | 0.831 | 0.824 | 0.827 | 0.886 |
| Random Forest | 0.879 | 0.868 | 0.861 | 0.864 | 0.912 |
| Gradient Boosting | 0.893 | 0.882 | 0.876 | 0.879 | 0.927 |
| Logistic Regression | 0.801 | 0.792 | 0.785 | 0.788 | 0.845 |

Table 2 summarizes the performance metrics of multiple supervised machine learning models used to classify cultural value system profiles. Among the evaluated models, the gradient boosting algorithm demonstrated the highest overall performance, achieving an accuracy of 0.893 and an AUC-ROC of 0.927, indicating excellent discriminative capability. The random forest model also performed robustly, with slightly lower but still high accuracy (0.879) and AUC-ROC (0.912), reflecting its effectiveness in capturing nonlinear relationships among cultural variables. The support vector machine achieved moderate-to-high performance, while logistic regression yielded comparatively lower metrics, suggesting that linear modeling approaches may be less capable of capturing the complex interactions underlying cultural value systems. The consistency across precision, recall, and F1-scores indicates balanced model performance with minimal bias toward specific classes. These findings highlight the superiority of ensemble-based machine learning approaches in modeling multidimensional cultural constructs.



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**Table 3**

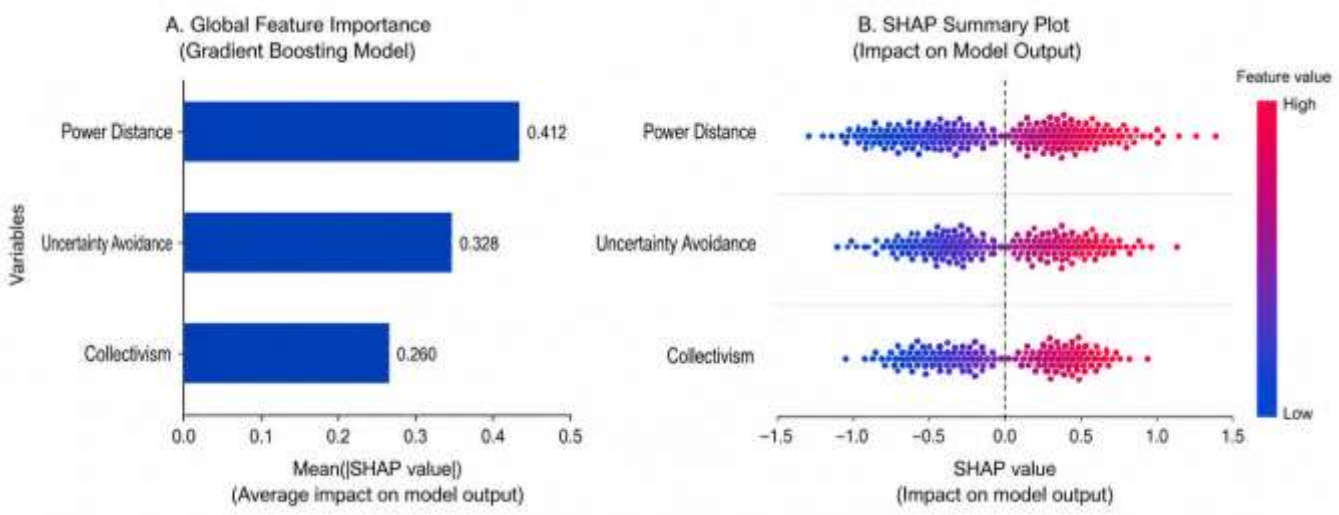
*Clustering Results and Cluster Characteristics (K-Means Solution)*

| Cluster | Collectivism | Power Distance | Uncertainty Avoidance | Cluster Size |
|---|---|---|---|---|
| 1 | 3.12 | 2.89 | 3.05 | 168 |
| 2 | 3.94 | 3.67 | 3.81 | 194 |
| 3 | 3.61 | 3.08 | 3.52 | 150 |

Table 3 presents the results of the k-means clustering analysis, which identified three distinct cultural value system profiles within the sample. Cluster 1 is characterized by relatively lower scores across all three dimensions, suggesting a more individualistic and low-hierarchy orientation with moderate tolerance for uncertainty. Cluster 2 exhibits the highest levels of collectivism, power distance, and uncertainty avoidance, representing a strongly structured and group-oriented cultural profile. Cluster 3 reflects moderate levels across all dimensions, indicating a hybrid cultural orientation that balances group affiliation with moderate acceptance of hierarchy and uncertainty. The distribution of participants across clusters indicates that the largest proportion belongs to Cluster 2, followed by Cluster 1 and Cluster 3. These findings demonstrate the presence of latent cultural subgroups within a national population, supporting the utility of unsupervised learning techniques in uncovering nuanced cultural patterns.

**Figure 1**

*Feature Importance of Cultural Variables in Predicting Value System Profiles*




**Panel A:** Global feature importance based on mean absolute SHAP values from the gradient boosting model. Higher values indicate greater overall influence on the prediction of cultural value system profiles.

**Panel B:** SHAP summary (beeswarm) plot showing the distribution of SHAP values for each variable. Each dot represents one participant. The position on the x-axis indicates the impact on model output (positive values increase the likelihood of belonging to the high-structure cultural cluster, negative values decrease it). The color of each dot represents the actual feature value (blue = low, red = high).

**Interpretation:** Power Distance is the most influential predictor, followed by Uncertainty Avoidance and Collectivism. Higher levels (red) of Power Distance and Uncertainty Avoidance tend to push predictions toward high-structure profiles, while lower levels (blue) contribute to low-structure profiles. Collectivism shows a moderating role with a narrower but meaningful impact.

The feature importance analysis derived from the gradient boosting model indicated that power distance was the most influential predictor of cultural value system classification, followed by uncertainty avoidance and collectivism. SHAP value distributions further revealed that higher levels of power distance contributed most strongly to classification into the high-structure cultural cluster, while lower levels were associated with more individualistic profiles.



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Uncertainty avoidance showed nonlinear contributions, with both very high and very low values exerting distinct predictive effects depending on interaction with other variables. Collectivism, while slightly less dominant, played a critical moderating role, particularly in differentiating between moderate and high collectivistic clusters. Overall, the figure illustrates the relative contribution and interaction effects of each variable, confirming that cultural value systems are shaped by a complex interplay of hierarchical acceptance, ambiguity tolerance, and group orientation.

## 4 Discussion

The present study aimed to model and identify cultural value systems using machine learning techniques grounded in the dimensions of collectivism, power distance, and uncertainty avoidance. The findings provide compelling evidence that these three dimensions not only exhibit meaningful interrelationships but also form coherent and distinguishable cultural profiles when analyzed using advanced computational approaches. The descriptive results indicated moderate variability across all three cultural dimensions within the Canadian sample, reinforcing the notion that cultural heterogeneity exists even within a single national context. This aligns with prior research emphasizing that national culture should not be treated as monolithic, but rather as a constellation of subcultural patterns shaped by demographic, social, and experiential factors (Bonjeer & Voňková, 2023; Zapata et al., 2022).

The observed positive correlations among collectivism, power distance, and uncertainty avoidance suggest that these constructs, while theoretically distinct, are empirically interconnected. In particular, the moderate association between collectivism and power distance indicates that individuals who prioritize group cohesion may also be more inclined to accept hierarchical social structures. This finding is consistent with prior studies demonstrating that collectivistic orientations often coexist with acceptance of authority and structured social roles, particularly in contexts where group harmony is maintained through hierarchical organization (Mohamed, 2024; Polatcan et al., 2025). Similarly, the relationship between uncertainty avoidance and power distance reflects a shared emphasis on stability, predictability, and control, which has been widely documented in cross-cultural research (Chen & Biswas, 2022; Shen et al., 2024). These interdependencies underscore the importance of examining cultural dimensions as part of an integrated system rather than as isolated variables.

The machine learning results further extend these insights by demonstrating that ensemble-based models, particularly gradient boosting and random forest algorithms, achieved superior performance in classifying cultural value system profiles. The high accuracy and AUC-ROC values observed for these models suggest that cultural values exhibit complex, nonlinear relationships that are better captured by flexible, data-driven approaches than by traditional linear models. This finding is consistent with recent research highlighting the advantages of machine learning in modeling multidimensional psychological and cultural constructs, where interactions and nonlinearities are prevalent (Ma et al., 2024; Wang et al., 2021). The comparatively lower performance of logistic regression further reinforces the limitations of conventional statistical techniques in capturing the nuanced interplay among cultural variables.

The clustering analysis revealed three distinct cultural profiles, characterized by low, moderate, and high levels of collectivism, power distance, and uncertainty avoidance. The identification of these clusters provides empirical support for the existence of latent cultural subgroups within a national population, challenging the assumption of cultural homogeneity. The high-structure cluster, characterized by elevated scores across all three dimensions, reflects a cultural orientation that prioritizes group cohesion, hierarchical order, and predictability. This profile is consistent with prior findings linking such cultural configurations to risk-averse behavior, strong institutional reliance, and preference for formalized social systems (Asiedu et al., 2023; Tong, 2024). In contrast, the low-structure cluster reflects a more individualistic, egalitarian, and flexible orientation, which has been associated with innovation, openness to change, and decentralized decision-making (Lee et al., 2022; Yeganeh, 2023). The moderate cluster represents a hybrid configuration, suggesting that individuals may simultaneously endorse elements of both structured and flexible cultural orientations depending on contextual demands.

The feature importance analysis provides further insight into the relative contribution of each cultural dimension in predicting value system profiles. Power distance emerged as the most influential predictor, followed by uncertainty avoidance and collectivism. This finding highlights the central role of hierarchical acceptance in shaping broader cultural orientations, suggesting that attitudes toward authority and inequality may serve as a foundational axis


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around which other cultural values are organized. This is consistent with prior research demonstrating the pervasive influence of power distance on organizational behavior, leadership expectations, and institutional trust (Polatcan et al., 2025; Tong, 2024). The strong contribution of uncertainty avoidance further emphasizes the importance of risk perception and tolerance for ambiguity in shaping cultural profiles, particularly in contexts characterized by rapid social and technological change (Dhingra et al., 2024; Shen et al., 2024). Collectivism, while slightly less dominant, played a significant moderating role, particularly in differentiating between intermediate and extreme cultural profiles.

These findings have important implications for understanding how cultural values influence behavior across domains. For instance, the identified cultural profiles may help explain variations in communication styles, decision-making processes, and organizational practices. In cross-cultural communication, individuals from high-structure profiles may prefer formal, hierarchical interactions, whereas those from low-structure profiles may favor informal and egalitarian exchanges (Li & Liu, 2024; Xu & Duan, 2023). Similarly, cultural value systems are likely to influence responses to digital technologies, marketing strategies, and public policies, as demonstrated in prior studies examining social media behavior, brand perception, and policy compliance (Mandela, 2024; Wang, 2025). The ability to accurately classify individuals into cultural profiles using machine learning thus has significant practical relevance for fields such as international business, public administration, and digital communication.

The results also contribute to the growing body of literature on the intersection of culture and innovation. The distinction between high-structure and low-structure cultural profiles suggests that cultural values may play a critical role in shaping attitudes toward innovation and technological adoption. Individuals with lower power distance and uncertainty avoidance may be more open to novel ideas and experimentation, whereas those with higher levels may prioritize stability and risk mitigation. This aligns with prior research linking cultural dimensions to innovation outcomes and technological engagement (Lee et al., 2022; Ma et al., 2024). Moreover, the hybrid nature of the moderate cluster suggests that cultural adaptability may be an important factor in navigating complex and rapidly changing environments.

From a methodological perspective, the study demonstrates the value of integrating machine learning techniques with established cultural frameworks. By leveraging advanced analytical tools, it is possible to uncover patterns and relationships that may not be detectable באמצעות traditional methods. This approach not only enhances predictive accuracy but also provides a more nuanced understanding of cultural dynamics, thereby advancing both theory and practice in the field. The use of interpretability techniques such as SHAP further strengthens the contribution of the study by providing transparent and theoretically meaningful explanations of model outputs.

## 5 Conclusion

Overall, the findings highlight the multidimensional and dynamic nature of cultural value systems and underscore the importance of adopting integrative, data-driven approaches to their study. By combining theoretical insights from cultural psychology with methodological innovations from machine learning, the present study offers a comprehensive framework for understanding cultural variation and its implications for behavior.

Despite its contributions, the present study is subject to several limitations. First, the cross-sectional design limits the ability to draw causal inferences regarding the relationships among cultural dimensions and behavioral outcomes. Second, the reliance on self-report measures introduces the possibility of response bias, particularly in the assessment of culturally sensitive constructs. Third, although the sample was diverse, it was confined to a single national context, which may limit the generalizability of the findings to other cultural settings. Additionally, while machine learning models provide strong predictive performance, they may be sensitive to sample characteristics and require careful validation across different populations. Finally, the study focused on three core cultural dimensions, and future research may benefit from incorporating additional variables to capture a more comprehensive representation of cultural value systems.

Future studies should consider employing longitudinal designs to examine the stability and evolution of cultural value systems over time. Expanding the scope of research to include multiple countries and cross-cultural comparisons would provide deeper insights into the universality and variability of the identified patterns. Additionally, integrating qualitative approaches could enrich the understanding of the contextual meanings underlying cultural dimensions. Researchers may also explore the inclusion of additional psychological, social, and contextual variables to enhance the explanatory power of machine



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learning models. Furthermore, the application of more advanced techniques, such as deep learning and network analysis, could provide new perspectives on the structure and dynamics of cultural systems.

The findings of this study have practical implications for policymakers, organizational leaders, and practitioners working in multicultural environments. Understanding cultural value profiles can inform the design of more effective communication strategies, leadership approaches, and organizational policies that align with the cultural orientations of target populations. In the context of global business, the ability to identify cultural patterns can enhance negotiation strategies, marketing campaigns, and customer engagement. In public policy, insights into cultural values can support the development of interventions that are culturally sensitive and more likely to achieve compliance and effectiveness. Finally, in educational and technological settings, recognizing cultural differences can contribute to the design of more inclusive and user-centered systems that accommodate diverse preferences and needs.

## Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

## Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

## Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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## Declaration of Interest

The authors report no conflict of interest.

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## Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

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