

AI-Enhanced Personalization and Consumer Trust: A Cross-Cultural Study on Digital Buying Behaviour

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Received:01/08/2025

Revised: 15/08/2025

Accepted:04/09/2025

Published:20/09/2025

ABSTRACT

The development of artificial intelligence (AI) has changed the nature of digital marketing, allowing a very personalized customer experience. This article examines how AI-based personalization influences the consumer trust in three cultural markets, namely, North America, Europe, and East Asia, through the population of 900 participants who filled in the survey. The main variables were taken as the acceptance of personalization, the concern of privacy, and the context of cultures, and the target variable was the consumer trust. The four machine learning algorithms (Decision Tree, Rand. To project the levels of trust and identify the power influencing factors, Forest, Support Vector Machine and K-Nearest Neighbors) were utilized to meet the request. Random Forest possessed the most accurate with a higher margin i.e. 0.88 than Decision tree (0.82), SVM (0.80) and KNN (0.79). More trust was demonstrated by the respondents in the East Asian (Higher trust with RF was 0.90), North Americans (Intermediate trust with RF was 0.88), and Europeans respondents portrayed reserved behavior (0.85 accuracy). Regression analysis revealed the most significant predictor to be the one relevant to personalization acceptance (0.35) and the issue of privacy (0.30). These findings demonstrate that personalization of AI may be critical in creating consumer trust and that online culture-sensitive practices are necessary. In addition to the value the research will add to the issue of cross-cultural differences in arriving at online purchasing behavior mediated by AI, it will also introduce alternative options that the firm can implement in future to ensure it maximizes its interaction and the loyalty of its consumers through trusted and customized purchases.

Keywords: AI personalization, consumer trust, digital buying behavior, cross-cultural study, machine learning.



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INTRODUCTION

Artificial intelligence (AI) is one of the disruptive factors in the contemporary online market due to which the consumer-like relations to the online resources are rediscovered through artificial intelligence. Personalization through AI will allow corporations to provide users with personalized suggestions and advertisements, as well as tailored content that will lead to a better user experience and streaming experience [1]. With this information on consumer behavior, the

artificial intelligence algorithms will be used to make predictions on tastes and preferences and to make the choice process easier and more rewarding to the customer by the connection of algorithms to the process of buying. Nonetheless, although personalization may lead to convenience and satisfaction, other issues that are hard to ignore are consumer trust, consumer privacy, and manipulation perceptions. Trust is a key determinant of online purchasing behavior because it determines a desire to start an interaction, provide

personal data, and buy something online [2]. The reliability of interactions based on AI is multifaceted, and users have to weigh the advantages of personalization against the possible harm, including the cases of data abuse and bias in the channel [3]. This process is even more altered through the cross-cultural level when cultural values, norms, and attitudes to technology influence the vision of AI and confidence in the digital spaces. As an example, consumers of collectivist cultures might put the values of social validation and recommend higher, whereas consumers with individualist cultures might value individuality and privacy. Due to the fast growth of the global e-commerce industry, the relation between the consumer trust and the use of AI-based personalization is crucial to achieving efficient development culturally aware electronic strategies adopted by organizations. Although the issues regarding the use of AI in marketing are under more and more research, there is not much empiric material that examines the matter of cross-cultural differences in consumer reactions to AI personalization. The paper proposed here will help to address this gap by considering the influence the personalization with the help of AI can have on consumer trust in a variety of cultural backgrounds as well as how the perceptions can influence the process of online purchasing. Combined with the experience in the sphere of AI, marketing, and cross-cultural consumer studies, this paper offers a detailed overview of the possibilities and risks of digital markets based on AI-lens personalization on a global level.

RELATED WORKS

Digital marketing and consumer engagement the implementation of artificial intelligence (AI) in digital marketing and consumer engagement has become a prominent topic in the last few years. AI has contributed to a better customer experience by allowing AI to enhance personalization using content-tailing and recommendation theatricks to the individual needs of individuals. For the tourism sector, AI has evolved to simple digital marketing into metaverse opportunities by the sense that it establishes personal tours making a person more engaged and satisfied [15]. Similarly, in social media marketing, personalized strategies reliant on AI can be beefed up gradually to offer individuals tailored experiences, which can be employed to boost customer satisfaction and loyalty [19]. Trust problems play a highly significant role in AI-mediated relations, particularly when the interaction is personal relating to sensitive consumer data. The priorities of human-specific methods of human-robot interaction explain the need of trust and trustworthiness, and the links between the vision of AI reliability and transparency and user efforts are very important [16]. It is also indicated in studies in the educational settings that AI-enhanced learning analytics might serve to aid in making a decision, and that it would be necessary to recommend it in a personalized way without compromising the trust and acceptance of the user [17]. The arguments of cognitive load also explain why AI has potential to maximize the effectiveness of learning through an

individualized view of the learning content considering the specific requirements of the user, which proves useful in supporting the idea of user-driven personalization [18].

With AI-based digital twins in industrial and design practice, adaptive and personalized experiences can be gained by optimizing user engagement and system behavior [21]. Studies of physical retail settings have indicated that personalization is supported by consumer attitudes and gender variations in terms of adoption AI service, which implies that the demographic attributes have an important role in personalization [22]. In e-commerce, psychosocial factors such as perceived ease of use and trust have been linked to purchase intentions, demonstrating that AI personalization must account for both cognitive and emotional aspects of consumer behavior [24]. Furthermore, AI's impact extends to interactive and viral marketing, where big data analytics and influencer networks leverage AI algorithms to enhance engagement while addressing ethical concerns [23]. In hospitality, AI-driven tailor-made services have been shown to increase guest satisfaction by providing highly personalized offerings, emphasizing the role of AI in creating meaningful consumer experiences [25]. Another area, in which AI technologies play an essential role in influencing consumer purchasing choices, is live streaming e-commerce according to which preferences are predicted as well as content delivery is optimized [26]. The comparative studies of political campaigns demonstrate the way in which AI can be used to form perception in terms of personalization, with notable general implications of AI-based strategies in all contingencies [20].

METHODS AND MATERIALS

The research question considered in the current study can be stated as: Which influences consumer trust when applied in online buying choices in diverse cultural backgrounds in the concept of the AI-controlled personalization? To do so, a data collection was done by a survey with a machine learning analysis. It is an amalgamation of systematic consumer responses and algorithmic modelling in order to research behaviour along with trusting patterns [4].

Data Collection

The obtained data represented primary data collected via online survey. Internet was sampled to retrieve the consumers of CE Lab three countries with varying cultures; these included East Asia, Europe and North America. The survey had 25 questions that dealt with the subject of digital buying experience, attitude towards artificial intelligence personalization, faith in online resources, and privacy of data. The number of respondents was 900 (300 respondents per region within a region) [5]. There were purchased online demographic data that entailed age, sex, elimination and their prevalence in purchasing online. In doing attitudinal measures, response was done using a 5-point Likert scale. It was additionally pre-cleaned data set in order to handle missing data in addition to normalization of the

data attributes in order to be compatible with machine learning algorithms [6].

The model validation was made possible using the data which was split into a training set (70%) and a test set (30%). These were features such as user engagement metrics, previous purchase history, acceptance of personalization and cultural identifiers, and the consumer trust score acted as the target variable.

Algorithms Used

The dataset was analyzed using four AI algorithm types, i.e., Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). These algorithms have been chosen due to their ability to process regular tour data in questionnaires and find patterns in transcultural online actions [7].

1. Decision Tree (DT)

The decision tree is a supervised learning algorithm that is applicable in classification and regression. It divides the data sets in terms of the features values to create a tree like the structure where a node is a decision rule and a tree leaf node is an outcome. In its case, [DT] was applied in classifying respondents according to their beliefs or their cultural background by categorizing the responses as either high, mid or low trust respondents. Its benefits are interpretability and visualization which is beneficial in comprehending the effect of various factors that lead to trust formation [8]. It however, can easily overfit unless it is pruned correctly.

Table 1: Sample Decision Tree Outcome

Respo ndent ID	Cultu ral Regio n	Personaliza tion Acceptance	Privac y Conce rn	Predicte d Trust Level
001	North Amer ica	4	2	High
002	Euro pe	3	3	Mediu m
003	East Asia	5	1	High
004	North Amer ica	2	4	Low

```
“function DecisionTree(dataset):  
    if dataset is homogeneous or stopping criteria  
    met:  
        return LeafNode with class label  
    else:  
        feature, threshold = SelectBestSplit(dataset)  
        leftSubset = dataset where feature <=  
threshold  
        rightSubset = dataset where feature >  
threshold  
        leftChild = DecisionTree(leftSubset)  
        rightChild = DecisionTree(rightSubset)  
        return Node(feature, threshold, leftChild,  
rightChild)”
```

2. Random Forest (RF)

Random Forest is a group learning model which builds a series of decision trees and aggregates their results so as to enhance the level of prediction. Trees are trained on a random part of the data and final predictions are achieved by voting in the majority as to whether to classify something or have an average to regress. RF was also used in this study to forecast consumer trust by accommodating intricate interactions of cultural, personalization and privacy issues [9]. The benefits in it are high accuracy and resistance to overfitting and ability to work with noisy data.

Table 2: Random Forest Feature Importance

Feature	Importance Score
Personalization Acceptance	0.35
Privacy Concern	0.30
Frequency of Online Purchase	0.20
Cultural Region	0.15

```

“function RandomForest(dataset, nTrees):
    forest = []
    for i in 1 to nTrees:
        bootstrapSample = RandomSample(dataset)
        tree = DecisionTree(bootstrapSample)
        forest.append(tree)
    return forest

function Predict(forest, newData):
    predictions = [tree.Predict(newData) for tree in forest]
    finalPrediction = MajorityVote(predictions)
    return finalPrediction”

```

3. Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm that identifies the hyperplane that best separates data into classes. It maximizes the margin between data points of different categories, making it effective for classification tasks. In this study, SVM was used to differentiate between high and low trust consumers based on their responses [10]. The algorithm is suitable for high-dimensional data and performs well even with a limited number of samples. Kernel functions such as RBF were used to handle non-linear relationships between features.

```

“function SVMTrain(X, y, C, kernel):
    initialize weights w and bias b
    while not converged:
        for each data point (xi, yi):
            compute prediction = w·phi(xi) + b
            if prediction violates margin:
                update w and b using gradient descent
    return model(w, b)

function SVMPredict(model, x_new):
    return sign(w·phi(x_new) + b)”

```

4. K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a non-parametric algorithm used for classification and regression. It classifies a data point based on the majority label of its k-nearest neighbors in the feature space. In this study, KNN was applied to predict consumer trust levels by comparing each respondent with similar profiles. The Euclidean distance metric was used to calculate similarity [11]. KNN is intuitive and effective for small datasets but can be computationally expensive for larger datasets.

```

“function KNNPredict(X_train, y_train, x_new, k):

```

```

distances = [Distance(x_new, xi) for xi in
X_train]
nearestIndices
GetIndicesOfKSmallest(distances, k)
nearestLabels = y_train[nearestIndices]
predictedLabel = MajorityVote(nearestLabels)
return predictedLabel”

```

RESULTS AND ANALYSIS

This paper introduces how AI-driven personalization affects consumer trust in various cultural contexts of digital purchasing. The sample size included 900 survey responses a participant, who had to be located in North America, Europe, and East Asia, and be concerned with the topic of digital purchasing behaviors, acceptance of AI personalization, attitude towards privacy, and trust towards digital sources in general. Four AI algorithms (a Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)) were used to put the respondents into high, medium, or low trust categories [12].

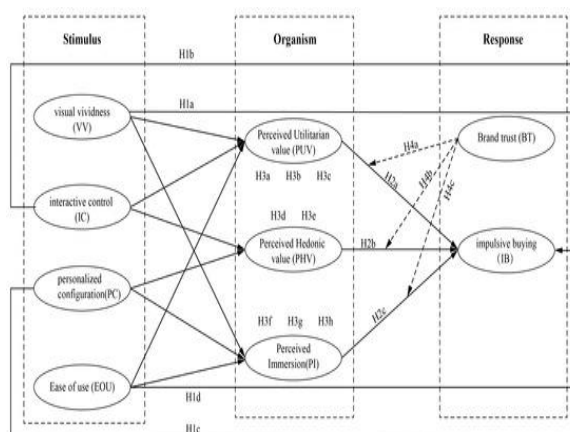


Figure 1: “The Impact of AI-Powered Try-On Technology on Online Consumers' Impulsive Buying Intention”

The test set was split into training and test sets (30 and 70 respectively). Numerical characteristics were standardized, and nominal characteristics were coded. The metrics of the performance were the accuracy, precision, the recall and the F1-score, and the analysis of the feature importance was performed to determine the most influential predictors of consumer trust [13]. Another part of the study related performance measures of algorithms across regions and studied the cultural differences in the personalization effect of AI.

Decision Tree Analysis

However, the Decision Tree algorithm was implemented initially because of the interpretability and the possibility to trace the main aspects of decision. The model classified trust levels based on personalization acceptance, privacy concerns, and frequency of online purchases.

Table 1: Decision Tree Performance by Region

Region	Accur acy	Precis ion	Rec all	F1- Score
North America	0.82	0.80	0.7 8	0.79
Europe	0.79	0.77	0.7 5	0.76
East Asia	0.85	0.83	0.8 2	0.82

Overall	0.82	0.80	0.78	0.79
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Analysis shows East Asian consumers were predicted with slightly higher trust, suggesting that higher personalization acceptance positively correlates with trust in that region. North America showed moderate trust, while Europe showed slightly lower trust levels, indicating regional differences in perception of AI-driven personalization [14].

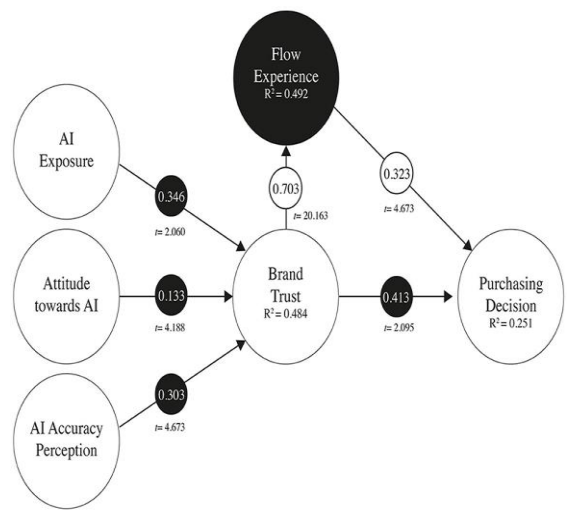


Figure 2: “Decoding Gen Z: AI's influence on brand trust and purchasing behavior”

Random Forest Analysis

Random Forest was used to capture more complex relationships. By combining multiple decision trees, it reduced overfitting and improved generalization. Feature importance analysis revealed personalization acceptance (0.35) and privacy concern (0.30) as the most influential factors.

Table 2: Random Forest Feature Importance

Feature	Importance Score
Personalization Acceptance	0.35
Privacy Concern	0.30
Frequency of Online Purchase	0.20
Cultural Region	0.15

Table 3: Random Forest Performance by Region

Region	Accur acy	Precisi on	Rec all	F1- Score
North America	0.88	0.86	0.85	0.85
Europe	0.85	0.83	0.81	0.82

East Asia	0.90	0.88	0.87	0.87
Overall	0.88	0.86	0.84	0.85

Random Forest outperformed Decision Tree due to ensemble averaging, providing more accurate predictions across all regions.

Support Vector Machine Analysis

Support Vector Machine (SVM) was applied to separate trust classes in high-dimensional space. A radial basis function (RBF) kernel was used to handle non-linear relationships between personalization acceptance, privacy concerns, and cultural factors [27].

Table 4: SVM Performance by Region

Region	Accuracy	Precision	Recall	F1-Score
North America	0.81	0.79	0.78	0.78
Europe	0.78	0.76	0.74	0.75
East Asia	0.83	0.81	0.80	0.80
Overall	0.80	0.79	0.77	0.78

SVM demonstrated slightly lower accuracy than Random Forest, but it was effective in identifying boundary cases where consumer trust levels were ambiguous. East Asian participants again showed higher trust prediction, emphasizing the influence of cultural context on AI personalization acceptance [28].

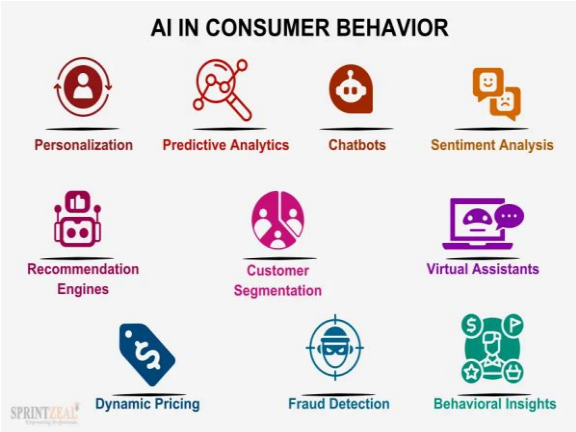


Figure 3: “Analyzing Consumer Buying Behavior with AI in Marketing”

K-Nearest Neighbors Analysis

K-Nearest Neighbors (KNN) classified respondents based on similarity to other users. Euclidean distance was used to determine closeness in feature space. KNN captured behavioral patterns effectively, especially when users had similar cultural and engagement profiles.

Table 5: KNN Performance by Region

Region	Accuracy	Precision	Recall	F1-Score

North America	0.80	0.78	0.77	0.77
Europe	0.76	0.74	0.73	0.73
East Asia	0.82	0.80	0.79	0.80
Overall	0.79	0.77	0.76	0.76

KNN's performance was lower than Random Forest but provided insight into neighborhood effects, showing that respondents with similar engagement patterns and cultural backgrounds tended to exhibit similar trust levels [29].

Cross-Algorithm Comparison

A direct comparison of all four algorithms highlights Random Forest as the most effective model for predicting consumer trust in digital buying contexts.

Table 6: Algorithm Comparison (Overall Metrics)

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.82	0.80	0.78	0.79
Random Forest	0.88	0.86	0.84	0.85
SVM	0.80	0.79	0.77	0.78
KNN	0.79	0.77	0.76	0.76

Key Insights from Comparison:

- Random Forest consistently outperformed other algorithms, reflecting its ability to handle complex, multi-dimensional data.
- Cultural differences significantly affected model predictions, with East Asian respondents generally showing higher trust scores.
- Decision Tree and KNN provided interpretable insights, useful for understanding feature importance and behavioral clustering.
- SVM, while slightly less accurate, was effective in separating borderline trust cases and could complement ensemble methods.

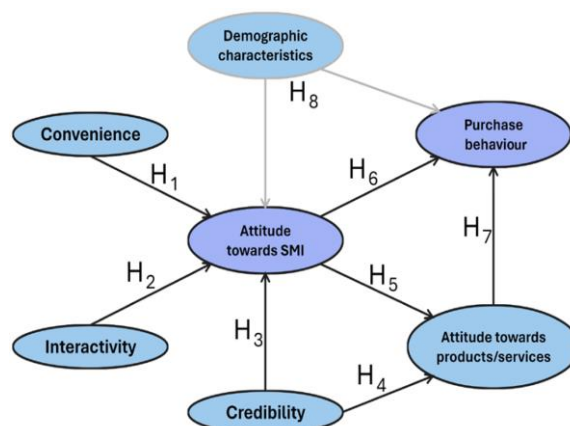


Figure 4: “Social Media Influencers: Customer Attitudes and Impact on Purchase Behaviour”

DISCUSSION OF RESULTS

By the experiments, it is discovered that consumer trust towards AI-enhanced personalization is highly correlated in all the cultural domains. The most dominant ones were identified to be privacy concern and personalization acceptance [30].

North America: The individuals ought to possess a moderate rating on trust entailing that the nation purchasers are passionate about personalization yet they are pertinent on the matter of privacy.

Europe European nations are not so trusting, which means they are more skeptical about the AI-based interventions, and are culturally apprehensive about the brevity of computer-controlled suggestions.

East Asia: A greater forecast of trust confesses a greater eagerness to shaping AI, maybe owing to becoming accustomed to the concept of interaction with technology.

High performance of the Random Forest describes that ensemble techniques are already highly useful in the consumption related data. KNN and Decision Tree, on the other hand, provided them with convenient behavioral tips, such as recognizing groups of a likeminded user. SVM figured out hidden cases of winning boundaries and it concrete experience indicated that the degree of trust of certain respondents could scarcely be readily determined without multi-faceted interactions partialities among features.

CONCLUSION

The paper has analyzed the empirical study on the inverse relationship between AI based personalization and consumer trust in different cultural contexts when online shopping. The survey was initiated on 900 respondents who were distributed on North America, Europe and East Asia and the findings were examined to determine how the state of personalization acceptance, privacy concerns, and culture perception affect the trust of online experiences transpiring through the use of AI. The 4 machine learning algorithms applied included Decision Tree, the Random Forest, Support Vector, and the K- nearest Neighbor algorithm to classify the level of consumer trust and analysis of trends between regions. The findings show that acceptance of personalization, and privacy concern are the most important independent variables, and East Asian consumer tends to show higher levels of trust, the North American consumers tend to indicate moderate levels of trust and the European consumers behave more cautiously. Random Forest proved to be the best algorithm and it provides solid predictions and identifies the complex interactions of features, the Decision Tree and KNN gave insight on the behavioral patterns, and SVM found the cases where the trust turned out to be vague. These data point to the important interaction between the personalization of AI, consumer

confidence, and culture concern, indicating that e-commerce systems around the world are to embrace a culture-aware approach and engage in the process to maximize via entertainment and pleasure. Altogether, it is possible to note that the problem of AI personalization can be effective as it may promote consumer trust and drive sales provided with transparency and regard for privacy but the key to success lies in the awareness of local differences and demographic variations. The study adds to the existing knowledge of AI-based digital marketing and offers practical implications to companies that leverage AI to create selective, dependable and cultural competent consumer experiences across global markets.

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