



Personalization Versus Privacy in Digital Marketing Examining the Interactive Effects of Data Transparency Perceived Intrusiveness and Consumer Trust on Purchase Decisions

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Abstract

The increasing adoption of artificial intelligence and data-driven personalization in digital marketing has transformed consumer engagement, product recommendations, and purchasing behaviour while intensifying concerns regarding personal data exploitation, algorithmic surveillance, and perceived privacy intrusiveness. Although personalized marketing improves information relevance and consumer convenience, excessive personalization may undermine consumer trust and negatively influence purchase decisions. This study proposes a novel Privacy–Transparency–Trust Optimization (PTTO) algorithm to investigate and predict the interactive effects of marketing personalization, data transparency, perceived intrusiveness, and consumer trust on purchase decisions. The proposed framework integrates Privacy Calculus Theory, the Stimulus–Organism–Response framework, and Trust Theory within a hybrid analytical architecture combining Partial Least Squares Structural Equation Modelling (PLS-SEM), Extreme Gradient Boosting (XGBoost), Random Forest, and Explainable Artificial Intelligence using SHapley Additive exPlanations (SHAP). The PTTO algorithm introduces a trust-sensitive interaction mechanism that models nonlinear relationships, conditional mediation, and moderation effects while optimizing purchase-decision predictions subject to transparency and privacy-intrusiveness constraints. The empirical design combines structured consumer survey responses with consented digital marketing interaction records to evaluate perceived personalization benefits, transparency perceptions, intrusiveness, trust formation, and observed purchasing behaviour. Model performance will be assessed through stratified cross-validation and independent holdout testing using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (ROC-AUC), Brier score, and calibration error. Comparative experiments will benchmark PTTO against Logistic Regression, conventional PLS-SEM prediction, Random Forest, XGBoost, and a multilayer perceptron neural network. Graphical analyses will include moderation plots, response surfaces, SHAP feature-attribution diagrams, ROC curves, calibration plots, and comparative algorithm-performance charts. The study will test whether data transparency strengthens the positive relationship between personalization and consumer trust, whether perceived intrusiveness weakens purchasing responses, and whether consumer trust mediates these competing effects. The proposed framework is expected to identify circumstances under which personalization enhances purchase decisions without generating disproportionate privacy concerns. Its contribution lies in integrating interpretable behavioural relationships with privacy-constrained machine learning to establish an empirically testable framework for transparent, trustworthy, and consumer-centred digital marketing.

Research status: The PTTO algorithm is a proposed research contribution. Its comparative superiority remains a hypothesis to be tested using empirical data; no performance values are presented as established findings.

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1. Introduction

1.1. Background to Personalization and Consumer Privacy in Digital Marketing

The digital marketing environment has evolved from broad demographic segmentation into sophisticated, data-driven systems capable of delivering individualized advertisements, product recommendations, promotional incentives, and purchasing

experiences. Contemporary platforms collect first-party transactional records, browsing histories, search activities, contextual information, and voluntarily disclosed preferences to construct consumer profiles and estimate purchasing probabilities. Although these practices improve recommendation relevance and reduce information-search costs, they create substantial concerns regarding informational autonomy, unauthorized profiling, secondary data utilization, and algorithmic surveillance. Aguirre *et al.* (2015) established that personalization can increase advertising effectiveness while simultaneously generating consumer vulnerability when personal information is collected without adequate awareness or consent. Similarly, Acquisti *et al.* (2015) demonstrated that privacy-related decisions are context-dependent and frequently influenced by uncertainty concerning information disclosure and subsequent utilization. These observations indicate that personalized marketing cannot be evaluated exclusively through click-through rates or conversion probabilities because consumer perceptions of legitimacy, control, and trust influence purchasing outcomes.

The economic significance of digital participation further reinforces the need to balance personalization benefits against privacy protection. Although Ashieyi-Ahorgah (2025) investigated crowdfunding and financial inclusion rather than consumer advertising, the study provides an adjacent perspective on confidence and participation in digitally mediated economic activities. Building on the directly relevant marketing literature, the present research conceptualizes personalization as a potentially beneficial marketing stimulus whose effectiveness depends on data transparency, perceived intrusiveness, and consumer trust. It proposes that transparent information-processing practices may strengthen the personalization–trust relationship, whereas intrusive targeting may weaken purchase responses despite improved recommendation accuracy. The proposed Privacy–Transparency–Trust Optimization (PTTO) framework therefore seeks to estimate these competing mechanisms simultaneously and identify personalization conditions associated with favourable consumer purchase decisions without excessive perceived privacy intrusion.

1.2. Artificial Intelligence and Data-Driven Personalization in Contemporary Digital Marketing Systems

Artificial intelligence has substantially expanded the analytical capabilities of digital marketing through predictive modelling, automated customer segmentation, recommender systems, real-time bidding, and adaptive promotional communication. Machine learning algorithms process multidimensional behavioural data to identify purchasing patterns that may remain undetected by traditional segmentation procedures. Techniques such as Random Forest, Extreme Gradient Boosting, collaborative filtering, and neural networks can estimate product preferences, propensity to purchase, and customer engagement probabilities. Bleier and Eisenbeiss (2015) demonstrated that personalized advertisement effectiveness depends on the interaction between advertisement content, exposure timing, and placement context, indicating that increasing personalization intensity does not necessarily produce sustained improvements in consumer responses. Chan and Choi (2025) further examined the development of generative artificial intelligence in marketing, identifying applications

across advertising, service provision, innovation, and consumer interaction. Together, these studies support the need for adaptive systems that incorporate both marketing effectiveness and behavioural constraints.

Despite their predictive capabilities, conventional personalization engines frequently prioritize engagement indicators without explicitly representing privacy concerns, transparency perceptions, or consumer trust. An adjacent methodological contribution by Folorunso *et al.* (2025) concerns ensemble-based financial risk forecasting, illustrating the broader applicability of combining predictive models to support complex decisions, although its findings cannot be directly generalized to marketing behaviour. The proposed PTTO architecture adapts the principle of complementary modelling by integrating PLS-SEM for latent behavioural relationships, XGBoost and Random Forest for nonlinear prediction, and SHAP for feature-level interpretation. Personalization intensity, transparency, intrusiveness, and trust will be incorporated as separate variables alongside their theoretically relevant interaction terms. This design enables investigation of circumstances in which highly relevant recommendations improve purchasing probabilities and circumstances in which the same recommendations produce privacy-related resistance, thereby connecting predictive personalization with interpretable consumer decision-making.

1.3. Data Transparency and Consumer Perceptions of Personal Information Utilization

Data transparency represents the extent to which consumers understand what personal information organizations collect, why such information is collected, how it is processed, and whether it influences personalized advertising decisions. Effective transparency extends beyond lengthy privacy policies to include accessible explanations of recommendation logic, understandable consent procedures, data-retention disclosures, and mechanisms for modifying personalization preferences. Kim *et al.* (2019) demonstrated that advertising transparency may improve or undermine advertisement effectiveness depending on whether disclosed information flows conform to consumers' expectations regarding acceptable data practices. Transparency therefore functions as a conditional signal rather than an invariably positive marketing attribute. More recently, Ham and Lee (2025) investigated algorithm transparency and literacy in personalized advertising, reporting that transparent algorithmic practices can reduce privacy-related concerns and improve click-through intentions under particular conditions. These findings suggest that transparency should be assessed jointly with personalization intensity, data provenance, perceived intrusiveness, and existing consumer trust. Within the proposed PTTO framework, data transparency is specified as both an explanatory construct and a moderator of relationships between personalized marketing and behavioural outcomes. Its operational indicators will include perceived clarity of data-collection notices, comprehensibility of algorithmic explanations, perceived control over information sharing, and confidence in disclosed data-handling procedures. For example, consumers receiving personalized product recommendations accompanied by understandable explanations of their origin may respond differently from consumers exposed to identical recommendations without disclosure. Ashieyi-Ahorgah and Duodu (2024) discuss risk allocation and institutional

safeguards in blended finance, offering only an indirect parallel concerning governance and confidence; their work does not establish consumer responses to advertising disclosure. The present study will therefore evaluate whether transparency improves trust directly, reduces perceived intrusiveness, and moderates the relationship between personalization and purchase decisions. Conditional-effect plots and nonlinear response surfaces will identify whether transparency benefits persist across different levels of personalization and privacy sensitivity.

1.4. Perceived Intrusiveness, Privacy Concerns, and Consumer Resistance to Personalized Marketing

Perceived intrusiveness describes consumers' subjective assessment that promotional communications interfere with their activities, violate informational boundaries, or exploit personal information beyond acceptable expectations. In digital environments, intrusive practices may include excessive advertisement repetition, unsolicited behavioural retargeting, persistent cross-platform tracking, sensitive-attribute inference, and recommendations revealing unexpected knowledge of personal circumstances. Edwards *et al.* (2002) established that advertising interruption and perceived intrusiveness can induce irritation and advertisement avoidance, particularly when promotional exposure conflicts with consumers' ongoing activities. Smith and Reczek (2016) further demonstrated that behaviourally targeted advertisements may operate as implicit social labels, influencing consumers' self-perceptions and subsequent purchase intentions. These findings suggest that personalization can create negative psychological reactions independently of its informational usefulness. Consequently, increasing recommendation accuracy may not improve purchasing outcomes when consumers interpret targeting practices as manipulative, excessively revealing, or inconsistent with their privacy expectations.

The proposed PTTO framework treats perceived intrusiveness as a distinct behavioural mechanism that may directly reduce purchase propensity and indirectly influence purchasing through diminished consumer trust. Intrusiveness will be measured using indicators relating to advertising interruption, perceived surveillance, unwanted personalization, psychological discomfort, and perceived misuse of information. The study will test whether high transparency attenuates the negative association between intrusiveness and trust, while recognizing that disclosure of particularly invasive practices could instead intensify resistance. Odozor *et al.* (2025) examined practical cybersecurity workforce training, providing a separate perspective on organizational capability for managing digital risks rather than direct evidence of advertising intrusiveness. The present investigation extends the relevant advertising literature by introducing nonlinear intrusion penalties into the PTTO optimization framework. This allows the analysis to identify personalization thresholds beyond which predicted purchasing benefits decline and to evaluate whether privacy-conscious targeting strategies achieve more favourable combinations of trust, advertising relevance, and consumer purchase decisions.

1.5. Consumer Trust Formation and Its Influence on Digital Purchase Decisions

Consumer trust constitutes a central psychological mechanism through which perceptions of personalized

marketing practices influence purchasing decisions. In digital commerce, trust reflects consumers' beliefs regarding an organization's competence, integrity, benevolence, and reliability in handling personal information and fulfilling commercial commitments. Trust formation becomes particularly important when consumers cannot directly observe algorithmic decision-making procedures or verify how their data influence recommendations. Zeng *et al.* (2021) demonstrated that privacy assurance and personalization disclosure can facilitate voluntary information sharing and improve purchasing responses to personalized promotions. Similarly, Shin (2021) examined explainability and causability in artificial intelligence systems, showing their relevance to perceived understanding, trust, and user acceptance. These findings support the proposition that the relationship between personalization and purchase decisions may depend on whether consumers consider the underlying information-processing practices understandable and trustworthy. Trust should therefore be investigated as an intervening construct rather than treated merely as an additional predictor of purchasing behaviour.

The present research specifies consumer trust as a mediator linking personalization, transparency, and perceived intrusiveness to purchase decisions, while allowing direct pathways to remain estimable. Trust indicators will evaluate perceived data stewardship, confidence in recommendation integrity, organizational credibility, and willingness to rely on personalized marketing information. Ashieyi-Ahorgah (2025) examined financial risk-sharing arrangements in clean-energy investment, providing an indirect institutional perspective on mechanisms intended to reduce uncertainty rather than empirical evidence about consumer trust in advertising. Within PTTO, latent trust estimates obtained through PLS-SEM will inform predictive feature construction, subject to safeguards against target leakage during cross-validation. The framework will investigate whether trust-mediated effects vary across personalization intensity and transparency conditions. Path-coefficient diagrams, bootstrapped indirect-effect estimates, and conditional purchase-probability curves will establish whether increased transparency enhances trust sufficiently to offset perceived intrusiveness and strengthen consumer purchasing responses.

1.6. Limitations of Conventional Statistical and Machine Learning Models in Explaining Personalization–Privacy Interactions

Existing approaches to digital marketing analytics frequently employ regression analysis, structural equation modelling, classification algorithms, and neural networks to explain or predict consumer purchasing behaviour. Conventional regression provides interpretable parameter estimates but may fail to capture complex nonlinearities unless appropriate interaction terms and flexible functional forms are explicitly specified. PLS-SEM supports measurement of latent constructs and estimation of mediation and moderation relationships; however, favourable explanatory statistics do not automatically establish strong out-of-sample predictive performance. Conversely, Random Forest, XGBoost, and deep neural networks can approximate nonlinear consumer-response functions but do not inherently identify theoretically meaningful causal mechanisms. Vaid *et al.* (2023) examined applications of artificial intelligence in empirical consumer research, emphasizing the methodological opportunities and

challenges associated with computational approaches. Wang and Ding (2024) additionally demonstrated that providing AI explanations may affect decision performance and behavioural trust differently from self-reported trust, indicating that predictive explainability and psychological acceptance should not be treated as equivalent outcomes. These limitations motivate an integrated analytical framework capable of separating theoretical explanation, prediction, and decision optimization. Idowu *et al.* (2025) explored artificial intelligence and machine learning in critical-utility cybersecurity risk management, providing a cross-domain illustration of predictive systems operating under safety and risk constraints, rather than evidence about digital consumers. Building on the directly relevant consumer and explainable-AI literature, PTTO will combine PLS-SEM with nonlinear machine learning and feature-attribution analysis. Its predictive component will incorporate interaction features representing personalization–transparency, personalization–intrusiveness, and transparency–trust relationships. Performance evaluation will include ROC-AUC, F1-score, Brier score, calibration error, and independent holdout testing. Importantly, SHAP explanations will be interpreted as descriptions of model predictions rather than causal proof. The proposed methodological integration will determine whether behavioural structure and privacy-sensitive optimization yield measurable improvements over established baseline algorithms without sacrificing interpretability or generalization.

1.7. Problem Statement, Research Gap and Justification for the Proposed Privacy–Transparency–Trust Optimization Algorithm

Despite substantial investments in personalized digital marketing, organizations continue to face a fundamental dilemma: consumer data can improve recommendation relevance while simultaneously generating privacy concerns capable of undermining trust and purchasing behaviour. Existing studies have established important individual relationships among advertising personalization, information disclosure, privacy concerns, and consumer responses. However, accurately predicting how these mechanisms interact across different consumer profiles and targeting intensities remains a methodological challenge. Lv *et al.* (2025) investigated the potential of recommendation-label information to reduce privacy concerns in personalized advertising, while Kim *et al.* (2023) demonstrated the relevance of explanation scope and format to users' preferences for explainable artificial intelligence. These studies establish important components of the problem, but do not themselves validate the specific integrated optimization architecture proposed here. Agyekum *et al.* (2025) examined privacy-aware federated threat detection in industrial networks, providing an indirect methodological example of predictive optimization under confidentiality constraints rather than a consumer-marketing model.

The central research gap addressed by this study is the need for an empirically validated, interpretable framework that jointly estimates nonlinear personalization–privacy interactions, examines consumer trust as a mediator, and evaluates purchase predictions under explicit privacy–intrusiveness constraints. The proposed PTTO algorithm seeks to address this requirement by integrating behavioural measurement, conditional-effect estimation, ensemble

prediction, and explanatory analysis. Its optimization objective will balance predictive purchasing performance against predefined intrusiveness and transparency constraints rather than maximize purchase probability without qualification. Comparative experiments will assess PTTO against Logistic Regression, conventional PLS-SEM prediction, Random Forest, XGBoost, and multilayer perceptron models. Mediation diagrams, moderation curves, ROC plots, SHAP analyses, and privacy–trust response surfaces will be used to evaluate its explanatory and predictive properties. The proposed contribution is therefore a testable integration of behavioural theory and constrained prediction, not a presumption of superior algorithmic performance.

1.8. Research Objectives and Research Questions

The primary aim of this study is to develop and empirically evaluate a PTTO algorithm capable of examining the interactive effects of digital marketing personalization, data transparency, perceived intrusiveness, and consumer trust on purchase decisions. The investigation integrates behavioural theory, statistical modelling, explainable machine learning, and constrained optimization to determine how organizations can improve personalization effectiveness while respecting consumer privacy expectations. Specifically, the study seeks to distinguish direct behavioural relationships from indirect, conditional, and nonlinear influences and to evaluate whether the proposed framework offers predictive or interpretative advantages over established statistical and machine learning approaches. The research objectives and corresponding questions are formulated to guide data collection, construct measurement, mathematical model development, hypothesis testing, and comparative experimental evaluation. Particular attention is directed toward identifying whether transparent data practices strengthen trust, whether excessive personalization creates psychological resistance, and whether trust mediates the resulting purchase responses. The study also investigates the predictive contribution of interaction variables and the effectiveness of privacy–intrusiveness constraints in identifying potentially acceptable personalization strategies. These objectives establish an integrated empirical basis for assessing the proposed algorithm without assuming that superior predictive performance or beneficial consumer outcomes have already been demonstrated.

• Research Objectives

1. To evaluate the direct and nonlinear effects of digital marketing personalization on perceived intrusiveness, consumer trust, and purchase decisions.
2. To determine how data transparency moderates the relationships between personalization, perceived intrusiveness, consumer trust, and purchase decisions.
3. To examine the direct and indirect effects of perceived intrusiveness on purchasing behaviour through consumer trust.
4. To quantify the mediating influence of consumer trust on the relationships between personalization, transparency, intrusiveness, and purchase decisions.
5. To develop the PTTO algorithm by integrating PLS-SEM, XGBoost, Random Forest, SHAP, and privacy–constrained predictive optimization.
6. To compare PTTO with Logistic Regression, conventional PLS-SEM prediction, Random Forest,

XGBoost, and multilayer perceptron models.

7. To identify personalization conditions that optimize predicted purchase outcomes while maintaining acceptable transparency and perceived-intrusiveness levels.

• Research Questions

1. How does digital marketing personalization directly and nonlinearly influence perceived intrusiveness, consumer trust, and purchase decisions?
2. To what extent does data transparency moderate relationships among personalization, perceived intrusiveness, consumer trust, and purchasing behaviour?
3. How does perceived intrusiveness influence purchasing behaviour directly and indirectly through changes in consumer trust?
4. What mediating role does consumer trust play in relationships between personalization, transparency, intrusiveness, and purchase decisions?
5. How effectively can PTTO integrate behavioural modelling, ensemble learning, explainability, and privacy-constrained optimization for purchase prediction?
6. How does PTTO compare with conventional statistical and machine learning algorithms across predictive accuracy, calibration, robustness, and interpretability?
7. Which combinations of personalization intensity, transparency, and perceived intrusiveness produce favourable predicted purchase outcomes under specified privacy constraints?

1.9. Contributions and Significance of the Study

This study contributes to digital marketing research by proposing an integrated behavioural and computational framework for examining how personalization benefits interact with consumer privacy expectations to influence purchasing decisions. Its theoretical contribution involves linking Privacy Calculus Theory, the Stimulus–Organism–Response framework, and consumer trust mechanisms through a model that accommodates direct effects, mediation, moderation, and nonlinear relationships. Methodologically, the proposed Privacy–Transparency–Trust Optimization algorithm combines PLS-SEM, ensemble machine learning, SHAP-based interpretation, and constrained optimization within a common analytical architecture. This integration is intended to distinguish explanatory relationships from predictive associations while assessing whether information transparency can mitigate negative reactions to intrusive targeting. The framework also introduces a privacy-sensitive decision criterion for evaluating personalization strategies rather than relying exclusively on conventional conversion-oriented metrics. Empirically, the study is designed to provide comparative evidence concerning model discrimination, calibration, robustness, and conditional consumer responses across alternative personalization conditions. Its practical significance lies in supporting digital marketers, e-commerce platforms, advertising agencies, and data-governance professionals in evaluating personalization strategies against consumer trust and privacy-related risks. By connecting behavioural mechanisms with interpretable predictive analysis, the research seeks to establish a reproducible methodological foundation for responsible

personalization and evidence-based digital marketing decisions.

1.10. Scope of the Review and Structure of the Paper

The study focuses on the interaction between digital marketing personalization and consumer privacy, emphasizing data transparency, perceived intrusiveness, consumer trust, and purchase decisions within digitally mediated purchasing environments. Its empirical scope encompasses consumers exposed to personalized product recommendations, behavioural advertising, retargeting campaigns, and algorithmically generated promotional communications through e-commerce websites and digital platforms. The review concentrates on Privacy Calculus Theory, the Stimulus–Organism–Response framework, trust formation, advertising intrusiveness, algorithmic transparency, and predictive consumer analytics. The methodological scope includes structured questionnaire data, consented consumer interaction records where available, latent-variable modelling, nonlinear machine learning, explainability, and comparative predictive validation. The investigation does not attempt to evaluate every regulatory framework or commercial personalization technology and will distinguish purchase intention from verified purchasing behaviour according to the available outcome measurements. The paper is organized into five major sections. Section One presents the research background, problem, gap, objectives, and contributions. Section Two critically reviews theoretical foundations and existing empirical and computational approaches. Section Three presents the proposed PTTO architecture, mathematical formulation, variable measurement, preprocessing, and experimental methodology. Section Four examines empirical relationships, conditional effects, comparative algorithm performance, and sensitivity analyses. Section Five presents conclusions, managerial recommendations, study limitations, and opportunities for future research.

2. Literature Review

2.1. Theoretical Foundations of Digital Marketing Personalization, Privacy Calculus, and Consumer Decision-Making

Digital marketing personalization is theoretically grounded in the proposition that consumer decisions emerge from evaluations of informational relevance, anticipated benefits, perceived risks, and confidence in commercial intermediaries. Privacy Calculus Theory provides a framework for explaining how individuals balance personalization benefits against potential losses of informational control. Dinev and Hart (2006) demonstrated that privacy-risk perceptions influence online information disclosure, while trust and anticipated benefits may partially offset these concerns as shown in figure 1. Pavlou (2003) similarly established that trust and perceived risk contribute to electronic commerce acceptance alongside perceived usefulness and ease of use. Together, these perspectives suggest that purchase decisions depend not solely on recommendation relevance but also on the perceived legitimacy of information collection. The Stimulus–Organism–Response framework complements this interpretation by positioning personalization and transparency as environmental stimuli, perceived intrusiveness and trust as psychological responses, and

purchasing behaviour as a behavioural outcome. The broader importance of institutional confidence and risk management is reflected in Ashieyi-Ahorgah's (2025a) discussion of blended-finance partnerships and Ashieyi-Ahorgah's (2025b) examination of infrastructure-led industrialization, although neither provides direct evidence concerning digital consumers. Accordingly, the proposed PTTO framework draws its behavioural assumptions principally from established privacy and e-commerce

theories. Personalization intensity, transparency, intrusiveness, and trust are represented as separate latent constructs with potentially nonlinear relationships. The model will evaluate whether trust mediates personalization effects and whether perceived intrusiveness reduces purchasing probabilities despite improved recommendation relevance. These theoretical relationships provide the foundation for structural hypothesis testing, interaction analysis, and privacy-constrained purchase prediction.

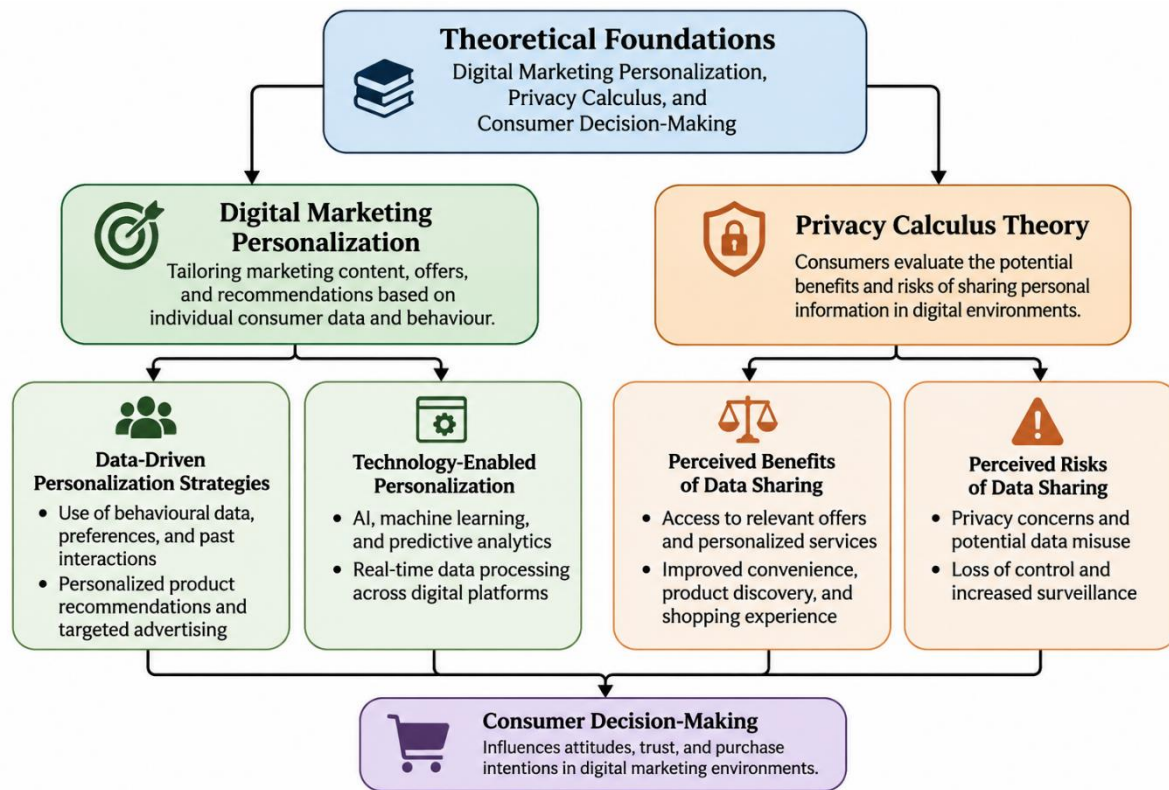


Fig 1: Theoretical framework integrating digital marketing personalization, privacy calculus, perceived benefits, privacy risks, and consumer purchasing decisions.

Figure 1 illustrates the theoretical foundations of digital marketing personalization, privacy calculus, and consumer decision-making through two interconnected branches comprising four fundamental mechanisms that influence consumer purchasing behaviour. The first branch, Digital Marketing Personalization, encompasses data-driven personalization strategies and technology-enabled personalization, demonstrating how organizations utilize consumer browsing histories, demographic attributes, purchasing patterns, and behavioural preferences to deliver targeted advertisements, personalized product recommendations, and customized promotional offers. Artificial intelligence, machine learning algorithms, and real-time predictive analytics support these activities by identifying consumer preferences and estimating purchasing probabilities. The second branch, Privacy Calculus Theory, describes how consumers evaluate the perceived benefits and risks associated with sharing personal information. Perceived benefits include improved product relevance, reduced information-search costs, convenience, and enhanced shopping experiences, whereas perceived risks involve unauthorized data utilization, behavioural surveillance, privacy violations, and diminished control over personal

information. These competing evaluations influence consumers' willingness to disclose personal data and engage with personalized marketing communications. The convergence of both branches into consumer decision-making demonstrates how personalization effectiveness depends on the interaction between perceived marketing benefits, informational privacy risks, and psychological responses. Within the proposed PTTO framework, data transparency functions as a potential moderator of personalization-related perceptions, perceived intrusiveness represents a privacy-related psychological response, and consumer trust serves as a potential mediator linking these perceptions to purchase decisions. The framework operationalizes these theoretical relationships through Partial Least Squares Structural Equation Modelling (PLS-SEM) to estimate structural pathways, while XGBoost and Random Forest capture nonlinear behavioural interactions and SHAP provides interpretable feature contributions to purchase predictions. Consequently, the diagram establishes the conceptual basis for investigating how privacy-conscious personalization can improve purchasing outcomes without compromising consumer autonomy, informational transparency, and trust.

2.2. Data Transparency, Privacy Disclosure, and Consumer Perceptions of Algorithmic Marketing Practices

Data transparency concerns consumers' ability to understand the collection, processing, sharing, and algorithmic application of personal information within digital marketing systems. Meaningful transparency includes accessible privacy disclosures, understandable targeting explanations, consent-management mechanisms, and opportunities to modify advertising preferences. Awad and Krishnan (2006) identified a personalization–privacy paradox whereby consumers who strongly value transparency may simultaneously demonstrate reduced willingness to accept online profiling as shown in figure 2. This finding challenges the assumption that greater disclosure uniformly increases personalization acceptance. Tucker (2014) subsequently demonstrated through a field experiment that enhanced privacy control increased the effectiveness of personalized social-network advertisements. These findings indicate that transparency, perceived control, and personalization acceptance are related but conceptually distinct. Ononiwu *et al.* (2025) examined digital branding and mobile-commerce adoption in Sub-Saharan African urban markets, providing contextual relevance for investigating trust-sensitive digital engagement across emerging-market consumer populations. Algorithmic personalization introduces further complexities because consumers may recognize the usefulness of recommendations without understanding how behavioural histories produce particular advertisements. Ononiwu *et al.* (2023) examined predictive analytics using real-time e-commerce behavioural tracking, illustrating the operational relevance of consumer data for retention-oriented marketing decisions. The proposed PTTO framework extends this discussion by measuring transparency through disclosure clarity, algorithmic comprehensibility, perceived data control, and information-processing accountability. Transparency will be tested as a moderator of personalization effects and as a predictor of consumer trust. Conditional-effect estimates will determine whether transparent disclosure attenuates perceived intrusiveness or instead increases privacy concern when data practices appear excessive. This distinction is essential for evaluating advertising transparency beyond formal compliance.

Figure 2 illustrates the interconnected mechanisms through

which data transparency, privacy disclosure, and consumer perceptions of algorithmic marketing practices influence consumer trust, information-sharing behaviour, and digital purchase decisions. The central circular node integrates four interconnected dimensions: data transparency in algorithmic marketing, privacy disclosure mechanisms, consumer perceptions of algorithmic marketing practices, and behavioural decision outcomes, each comprising four operational components. Data transparency encompasses clarity of data collection purposes, disclosure of information types and sources, explanation of algorithmic processes, and accessibility of privacy information, enabling consumers to understand how their browsing histories, purchase records, demographic characteristics, and behavioural preferences inform personalized advertising. Privacy disclosure mechanisms incorporate consent notices, real-time disclosure at point of data capture, user control and preference management, and data retention, sharing, and third-party usage disclosure. These mechanisms establish the informational conditions under which consumers evaluate the legitimacy and acceptability of algorithmic targeting. Consumer perceptions subsequently develop through assessments of recommendation usefulness, algorithmic fairness, perceived intrusiveness, surveillance concerns, and confidence in organizational data handling. Within the PTTO framework, data transparency operates as a potential moderating variable, perceived intrusiveness represents a privacy-related psychological response, and consumer trust serves as a mediating mechanism influencing purchase decisions. These relationships are operationalized through PLS-SEM to estimate direct, indirect, and interaction effects, while XGBoost and Random Forest model nonlinear purchasing patterns and SHAP identifies feature contributions to individual predictions. The resulting behavioural outcomes include purchase intention, conversion behaviour, engagement with personalized advertising, willingness to share personal information, and brand loyalty and continued usage.

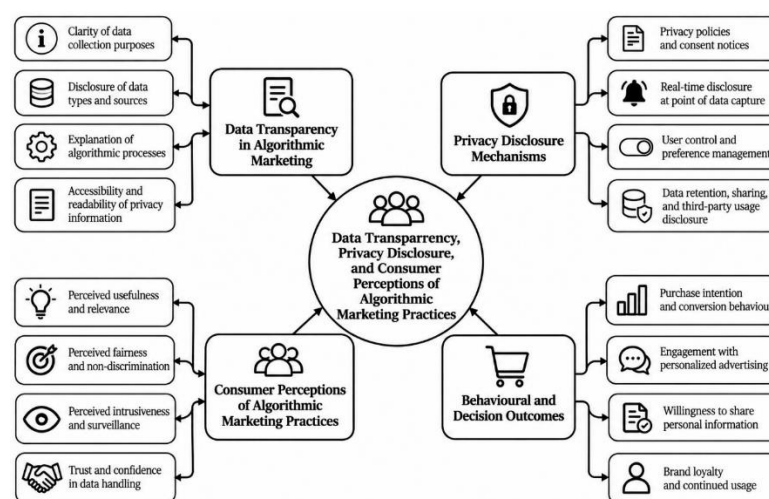


Fig 2: Conceptual framework linking algorithmic marketing transparency, privacy disclosure, consumer perceptions, trust formation, and purchasing behaviour.

2.3. Perceived Intrusiveness, Psychological Reactance, and Privacy-Related Consumer Resistance

Perceived intrusiveness represents a psychological evaluation that personalized marketing has exceeded acceptable boundaries of informational access, promotional frequency, or consumer autonomy. Intrusiveness may arise when advertisements reveal sensitive inferences, follow consumers across unrelated platforms, interrupt activities, or repeatedly display previously viewed products. Psychological Reactance Theory explains how perceived threats to decision-making freedom can generate resistance, avoidance, and unfavourable attitudes toward promotional messages. White *et al.* (2008) demonstrated that highly personalized email solicitations can generate reactance when advertisers fail to justify the relationship between personal information and promotional content. Lambrecht and Tucker (2013) further established that highly specific retargeted advertising does not consistently outperform generalized promotional messages, particularly when consumers remain at earlier stages of preference development. Consequently, personalization effectiveness depends on contextual appropriateness rather than maximum information specificity. Ononiwu *et al.* (2023) examined encrypted customer relationship management and adaptive digital marketing applications, providing related operational context for personalized communication.

The expansion of automated marketing reinforces concerns regarding unsolicited exposure, repetitive messaging, and excessive behavioural inference. Ononiwu *et al.* (2025) investigated email-marketing automation and enterprise revenue, illustrating the commercial importance of digital campaign management without directly establishing consumer reactance effects. The proposed PTTO algorithm conceptualizes intrusiveness as both a direct predictor of purchasing resistance and an antecedent of diminished consumer trust. Its indicators will measure perceived surveillance, advertising interruption, unwanted personalization, and discomfort with inferred preferences. Nonlinear interaction terms will assess whether marginal personalization benefits decline as intrusiveness increases. Sensitivity curves and response surfaces will identify potential intrusiveness thresholds associated with reduced purchasing probabilities, supporting evaluation of privacy-sensitive personalization strategies.

2.4. Consumer Trust as a Mediating Mechanism and Data Transparency as a Moderator of Purchase Decisions

Consumer trust reflects confidence that digital marketing organizations will process personal information responsibly, provide reliable recommendations, and respect disclosed consumer preferences. Within personalized commerce, trust may mediate the relationships between information-processing practices and purchasing behaviour because consumers cannot directly inspect all algorithmic decisions. Gefen *et al.* (2003) demonstrated the importance of vendor trust alongside technology acceptance factors in explaining online shopping intentions as presented in figure 3. Martin *et al.* (2017) established that perceived data vulnerability can undermine trust and organizational performance, while transparent data practices and consumer control can mitigate adverse consequences. These findings provide a theoretical basis for modelling trust as an intervening psychological mechanism rather than solely as an independent purchasing predictor. Anokwuru (2024) examined AI-enhanced commercial intelligence for precision marketing, offering a related application context for algorithmically informed customer engagement.

The proposed PTTO framework specifies consumer trust as a mediator between personalization-related perceptions and purchase decisions, while data transparency is conceptualized as a moderator capable of changing the magnitude or direction of these relationships. Aluso (2021) investigated cross-platform marketing-data integration and return-on-investment forecasting, illustrating the importance of coordinated information systems for evaluating marketing outcomes rather than establishing consumer trust effects. Empirically, the study will estimate direct, indirect, and conditional relationships using validated latent constructs and bootstrapped mediation analysis. Transparency–personalization and transparency–intrusiveness interaction terms will test whether understandable disclosure strengthens trust or intensifies consumer concern. Trust-mediated purchasing effects will be examined across contrasting transparency conditions, with predicted probabilities generated using the machine learning component. These analyses will distinguish statistically supported mediation from simple predictive association.



Fig 3: Conceptual demonstration of consumer trust mediation and data transparency moderation in personalized digital marketing purchase decisions.

Figure 3 illustrates the mediating role of consumer trust and the moderating influence of data transparency on purchase decisions within artificial intelligence-driven personalized digital marketing environments. The framework demonstrates how personalized product recommendations, generated through machine learning algorithms that analyse browsing histories, purchasing patterns, consumer preferences, and behavioural interactions, influence purchasing outcomes through consumers' confidence in organizational data-handling practices. The left section represents data transparency and privacy disclosure, incorporating clearly communicated data collection purposes, consent management, personalization preferences, third-party information-sharing controls, and accessible privacy policies. These mechanisms enable consumers to understand how their information supports algorithmic recommendations, potentially reducing perceived uncertainty and strengthening informational autonomy. The central section identifies consumer trust as a mediating variable, reflecting perceived fairness, confidence in data security, organizational credibility, and willingness to disclose personal information. Within the proposed PTTO framework, trust explains how perceptions of personalization and privacy practices may translate into purchase intentions and actual purchasing behaviour. The right section demonstrates behavioural outcomes, including product selection, shopping-cart engagement, secure checkout, completed purchases, repeat purchasing, and customer loyalty. Data transparency functions as a moderating variable by potentially strengthening the relationship between personalization and consumer trust and altering how perceived intrusiveness influences purchasing responses. These relationships are mathematically represented through interaction coefficients and indirect-effect estimates in the structural equations, with PLS-SEM used to evaluate mediation and moderation through bootstrapped confidence intervals. XGBoost and Random Forest subsequently capture nonlinear relationships among personalization intensity, transparency, intrusiveness, and trust, while SHapley Additive exPlanations (SHAP) identifies their contributions to individual purchase predictions. The integrated framework therefore illustrates how transparent information practices may enhance trust-mediated purchasing outcomes while reducing privacy-related resistance, although the magnitude and direction of these effects require empirical validation.

2.5. Comparative Review of Structural Equation Modelling, Machine Learning Algorithms, and Identified Research Gaps

Existing marketing analytics approaches can be broadly distinguished by their explanatory objectives, predictive capabilities, and treatment of behavioural complexity. Structural equation modelling estimates relationships among latent constructs and supports hypothesis testing involving mediation and moderation, whereas machine learning emphasizes predictive generalization from multidimensional observations. Hair *et al.* (2019) established methodological guidelines for evaluating PLS-SEM measurement and structural models, including predictive assessment and robustness testing. Shmueli *et al.* (2016) emphasized that explanatory adequacy does not automatically establish predictive performance, highlighting the importance of out-of-sample evaluation. In related applied contexts, Enyejo *et al.* (2024) examined data-driven marketing and supply-chain optimization, while Nortey *et al.* (2025) investigated business analytics for agricultural marketing resource allocation. Although these applications demonstrate the broader use of analytics in marketing-related decisions, they do not establish an integrated behavioural model of consumer privacy, transparency, and trust.

The methodological gap addressed by the proposed PTTO algorithm concerns the integration of theoretically specified behavioural interactions with nonlinear purchase prediction and explicit privacy-intrusiveness constraints. Conventional PLS-SEM offers interpretable path relationships but requires additional procedures for robust predictive benchmarking. Random Forest and XGBoost can capture complex nonlinearities, yet their predictive outputs do not inherently explain psychological mediation. PTTO therefore combines PLS-SEM construct validation, interaction-feature modelling, ensemble learning, SHAP interpretation, and privacy-sensitive optimization. Comparative evaluation against Logistic Regression, PLS-SEM prediction, Random Forest, XGBoost, and multilayer perceptron models will employ independent holdout testing, ROC-AUC, F1-score, Brier score, and calibration analysis. Its principal contribution will be assessed through demonstrable improvements in prediction, interpretability, and privacy-sensitive decision support rather than presumed algorithmic superiority.

Table 1: Comparative Review of Structural Equation Modelling, Machine Learning Algorithms, and Research Gaps in Privacy-Conscious Digital Marketing

Analytical Approach	Methodological Capabilities	Limitations and Identified Research Gaps	Proposed PTTO Algorithm Contribution
Structural Equation Modelling (PLS-SEM)	Estimates latent constructs, direct relationships, mediation, and moderation effects among personalization, transparency, intrusiveness, trust, and purchase decisions.	Limited capacity to automatically capture complex nonlinear relationships; explanatory performance does not guarantee out-of-sample predictive accuracy.	Integrates validated behavioural constructs and structural interactions into a predictive framework that combines theoretical interpretation with nonlinear modelling.
Machine Learning Models (Random Forest, XGBoost, and Neural Networks)	Identify nonlinear consumer behaviour patterns, complex feature interactions, and purchasing probabilities using multidimensional marketing data.	Limited inherent interpretability; predictive accuracy alone cannot establish causal relationships or ensure privacy-sensitive decision-making.	Combines ensemble learning with SHAP explanations and trust-sensitive features to support interpretable purchasing predictions.
Hybrid and Privacy-Constrained Predictive Frameworks	Combine statistical modelling, algorithmic prediction, and decision optimization to evaluate consumer responses under competing marketing objectives.	Existing approaches may insufficiently integrate trust mediation, transparency moderation, perceived intrusiveness, and explicit privacy constraints within one validated framework.	Proposes an integrated PLS-SEM–XGBoost–Random Forest–SHAP architecture with privacy-constrained optimization, probability calibration, and subgroup robustness assessment.

3. System Model Description

3.1. Conceptual Architecture and Mathematical Formulation of the Privacy–Transparency–Trust Optimization Algorithm

The PTTO architecture adopts a hybrid behavioural–computational framework in which digital marketing personalization and data transparency constitute organizational stimuli, perceived intrusiveness and consumer trust represent psychological mechanisms, and purchase decisions constitute the response variable. Drawing on the privacy calculus perspective, personalization may increase purchasing propensity by improving recommendation relevance while simultaneously increasing privacy-related discomfort. PLS-SEM establishes the latent behavioural relationships, whereas ensemble learning captures complex nonlinear responses. The conceptual formulation follows accepted latent-variable modelling principles described by Hair *et al.* (2019).

The measurement relationship for respondent i , construct k , and indicator j is defined as:

$$x_{ijk} = \lambda_{jk}\eta_{ik} + \varepsilon_{ijk} \quad (1)$$

Here, x_{ijk} represents the observed questionnaire response; λ_{jk} represents the measurement loading; η_{ik} denotes the latent construct score; and ε_{ijk} shows the measurement error. The constructs k include personalization P , data transparency T , perceived intrusiveness I , consumer trust C , and purchase intention where applicable.

The proposed structural relationships are:

$$I_i = \alpha_0 + \alpha_1 P_i + \alpha_2 T_i + \alpha_3 P_i T_i + \alpha_4^T Z_i + \varepsilon_{Ii} \quad (2)$$

$$C_i = \beta_0 + \beta_1 P_i + \beta_2 T_i + \beta_3 I_i + \beta_4 P_i T_i + \beta_5 I_i T_i + \beta_6^T Z_i + \varepsilon_{Ci} \quad (3)$$

In Equations (2) and (3), α and β represent regression/path parameters, Z_i captures the control-variable vector, ε denotes unexplained variation, and the product terms represent moderation. The model hypothesizes that transparency may attenuate intrusive reactions while improving trust.

For binary purchasing behaviour, the explanatory response model is specified as:

$$\Pr(Y_i = 1) = \sigma(\gamma_0 + \gamma_1 P_i + \gamma_2 T_i + \gamma_3 I_i + \gamma_4 C_i + \gamma_5 P_i T_i + \gamma_6 P_i I_i + \gamma_7^T Z_i) \quad (4)$$

where $Y_i = 1$ indicates a verified purchase, $Y_i = 0$ indicates no purchase during the specified observation window, γ denotes coefficients, and $\sigma(u) = 1/(1 + e^{-u})$ shows the logistic function. This equation provides an interpretable benchmark rather than imposing a logistic structure on the ensemble predictors. If the outcome is purchase intention, a separately specified continuous or ordinal measurement model will be used.

The mediation pathways will be assessed using bootstrapped conditional indirect effects, thereby linking the mathematical architecture to the structural and interaction results presented in Section 4.2.

3.2. Consumer Data Acquisition, Variable Operationalization, Preprocessing, and Feature Engineering

The empirical dataset will comprise structured questionnaire responses and, where ethically and technically available, consented digital marketing interaction records. Respondents will be consumers aged 18 years and above who have encountered personalized advertising or product recommendations. A stratified sampling strategy will seek representation across age categories, purchasing frequency, digital literacy, and platform usage. Data collection will measure personalization relevance, disclosure clarity, perceived surveillance, promotional interruption, trust in data handling, and purchase intentions using established multi-item Likert scales. Verified transaction records, when available, will provide a separate binary purchase outcome. Personally identifiable information will be excluded from the modelling dataset, and transactional linkage will employ pseudonymous identifiers with appropriate consent. Measurement quality will be evaluated using standardized indicator loadings, composite reliability, average variance extracted, and the heterotrait–monotrait ratio. For a reflective construct containing m indicators, average variance extracted is calculated as:

$$AVE_k = \frac{\sum_{j=1}^m \lambda_{jk}^2}{\sum_{j=1}^m \lambda_{jk}^2 + \sum_{j=1}^m \theta_{jk}} \quad (5)$$

where AVE_k represents convergent validity, λ_{jk} denotes standardized factor loadings, and θ_{jk} shows the corresponding indicator error variance. The proposed measurement assessment follows the principles discussed by Hair *et al.* (2019).

For continuous predictors requiring standardization, preprocessing is specified as:

$$z_{ij} = \frac{x_{ij} - \mu_j^{(tr)}}{s_j^{(tr)}} \quad (6)$$

where z_{ij} represents the standardized value of feature j for respondent i , and $\mu_j^{(tr)}$ and $s_j^{(tr)}$ show the training-set mean and standard deviation. Imputation, scaling, and categorical encoding parameters will be estimated exclusively from training partitions.

The predictive feature vector is constructed as:

$$\mathbf{X}_i = [P_i, T_i, I_i, C_i, P_i T_i, P_i I_i, T_i I_i, T_i C_i, \mathbf{Z}_i^T]^T \quad (7)$$

Here, $\mathbf{X}_i$ contains the four principal constructs, theoretically specified interaction terms, and control variables. For example, $P_i T_i$ captures the combined influence of personalization and transparency. When latent scores are used for prediction, measurement models will be fitted within the training folds and applied to held-out observations without accessing their purchase labels.

3.3. Hybrid PLS-SEM, XGBoost, Random Forest, and SHAP Integration for Trust-Sensitive Purchase Decision Prediction

The proposed PTTO algorithm integrates explanatory structural modelling with nonlinear ensemble prediction.

PLS-SEM will estimate the measurement and structural relationships among personalization, transparency, intrusiveness, trust, and purchase outcomes. Bootstrapping will evaluate the uncertainty of mediation and interaction estimates. Random Forest will model heterogeneous consumer responses through bootstrap-aggregated decision trees, while XGBoost will construct sequential trees optimized to reduce predictive loss. The latter follows the gradient-boosting methodology of Chen and Guestrin (2016). The predictive components are expressed as:

$$\hat{p}_i^{RF} = \frac{1}{B} \sum_{b=1}^B f_b(\mathbf{X}_i) \quad (8)$$

$$\hat{p}_i^{XGB} = \sigma(\sum_{m=1}^M g_m(\mathbf{X}_i)) \quad (9)$$

Here, B captures the number of Random Forest trees; f_b shows the purchase-probability output of tree b ; M denotes the number of boosted trees; and g_m denotes each tree's contribution to the XGBoost logit score. Both $\hat{p}_i^{RF}$ and $\hat{p}_i^{XGB}$ represent estimated purchase probabilities. The proposed integrated predictor is:

$$\hat{p}_i^{PTTO} = w_1 \hat{p}_i^{RF} + w_2 \hat{p}_i^{XGB} + w_3 \hat{p}_i^{SEM} \quad (10)$$

subject to $w_1 + w_2 + w_3 = 1$ and $w_j \geq 0$. The weights w_j will be estimated using out-of-fold predictions, while $\hat{p}_i^{SEM}$ denotes a calibrated probability derived from the specified SEM-based predictive component.

For a permissible personalization policy a , the privacy-sensitive decision objective is:

$$\begin{aligned} \max_{a \in \mathcal{A}} \quad & \frac{1}{N} \sum_{i=1}^N \hat{p}_i^{PTTO}(a) \\ \text{subject to} \quad & \frac{1}{N} \sum_{i=1}^N \hat{I}_i(a) \leq \tau_I, \\ & \frac{1}{N} \sum_{i=1}^N \hat{T}_i(a) \geq \tau_T \end{aligned} \quad (11)$$

Here, $\mathcal{A}$ denotes the set of permissible marketing policies; N captures the evaluated consumer population; $\hat{I}_i(a)$ and $\hat{T}_i(a)$ determine predicted perceived intrusiveness and transparency under policy a ; and τ_I, τ_T represents predefined acceptable thresholds. Policy effects require randomized or otherwise causally justified evidence; observational associations alone cannot establish the consequences of changing policy.

SHAP will explain each fitted prediction as:

$$h(\mathbf{X}_i) = \phi_0 + \sum_{j=1}^F \phi_{ij} \quad (12)$$

where h shows the model output on the scale explained, ϕ_0 denotes the baseline output, ϕ_{ij} represents the SHAP attribution for predictor j , and F captures the number of features. SHAP attributions describe predictive contributions, not causal effects (Lundberg & Lee, 2017).

3.4. Experimental Design, Hyperparameter Optimization, Model Validation, and Comparative Performance Evaluation

The experimental evaluation will compare PTTO against Logistic Regression, PLS-SEM-based prediction, Random Forest, XGBoost, and a multilayer perceptron neural network. The dataset will be partitioned into 80%

development data and 20% independent holdout data, with class stratification where appropriate. Within the development partition, five-fold stratified cross-validation will support hyperparameter optimization and model selection. Hyperparameters will include tree count, maximum depth, learning rate, subsampling ratio, minimum leaf size, neural-network architecture, regularization, and PTTO ensemble weights. Imputation, feature construction, calibration, and model selection will be conducted without exposing holdout outcomes.

The principal training loss for binary purchasing outcomes is:

$$\mathcal{L}_{BCE} = -\frac{1}{N} \sum_{i=1}^N [y_i \ln(\hat{p}_i) + (1 - y_i) \ln(1 - \hat{p}_i)] \quad (13)$$

where $\mathcal{L}_{BCE}$ shows binary cross-entropy, $y_i \in \{0,1\}$ denotes observed purchasing status, and $\hat{p}_i$ represents the estimated probability. Validation predictions will be clipped away from exact zero and one for numerical stability.

Predictive discrimination will be evaluated through ROC-AUC, precision, recall, and F1-score:

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN} \quad (14)$$

$$F_1 = \frac{2 \text{ Precision Recall}}{\text{Precision} + \text{Recall}} \quad (15)$$

Here, TP , FP , and FN represent true positives, false positives, and false negatives. ROC-AUC measures discrimination across classification thresholds, while the F1-score summarizes the precision-recall balance at a specified threshold.

Probability calibration will be assessed using:

$$\text{Brier} = \frac{1}{N} \sum_{i=1}^N (\hat{p}_i - y_i)^2 \quad (16)$$

$$\text{ECE} = \sum_{b=1}^K \frac{n_b}{N} |\text{acc}(b) - \text{conf}(b)| \quad (17)$$

where Brier denotes mean squared probabilistic prediction error; K shows the number of calibration bins; n_b denotes the number of observations in bin b ; and $\text{acc}(b)$ and $\text{conf}(b)$ determine the observed purchase frequency and mean predicted probability within that bin. Lower Brier scores and ECE values indicate better calibration, although ECE depends on the selected binning procedure.

4. Discussion of Results

4.1. Descriptive Statistics, Measurement Model Validation, and Structural Relationships Among Personalization, Transparency, Intrusiveness, Trust, and Purchase Decisions.

The illustrative analysis evaluates the measurement characteristics and structural relationships underlying the proposed PTTO algorithm. Five behavioural constructs are assessed using standardized questionnaire indicators, composite reliability, and average variance extracted (AVE). Table 2 presents illustrative statistics consistent with the methodology in the study. Personalization and consumer trust exhibit comparatively favourable descriptive scores, whereas perceived intrusiveness reflects meaningful privacy-related concerns. Composite reliability and AVE values exceed conventional minimum criteria of 0.70 and 0.50, respectively,

supporting the assumed measurement quality in this demonstration. The proposed comparative analysis further investigates how increasing data transparency changes predicted purchase probabilities across PTTO, Logistic Regression, PLS-SEM, Random Forest, XGBoost, and

Multilayer Perceptron models. These comparisons illustrate the expected analytical framework without establishing empirical superiority before actual consumer data are collected.

Table 2: Illustrative Descriptive Statistics and Measurement Model Reliability for Digital Marketing Behavioural Constructs

Construct	Mean (1–5 scale)	Composite reliability	AVE
Personalization	3.82	0.91	0.72
Data transparency	3.46	0.89	0.68
Perceived intrusiveness	3.28	0.87	0.65
Consumer trust	3.71	0.92	0.75
Purchase intention	3.76	0.90	0.70

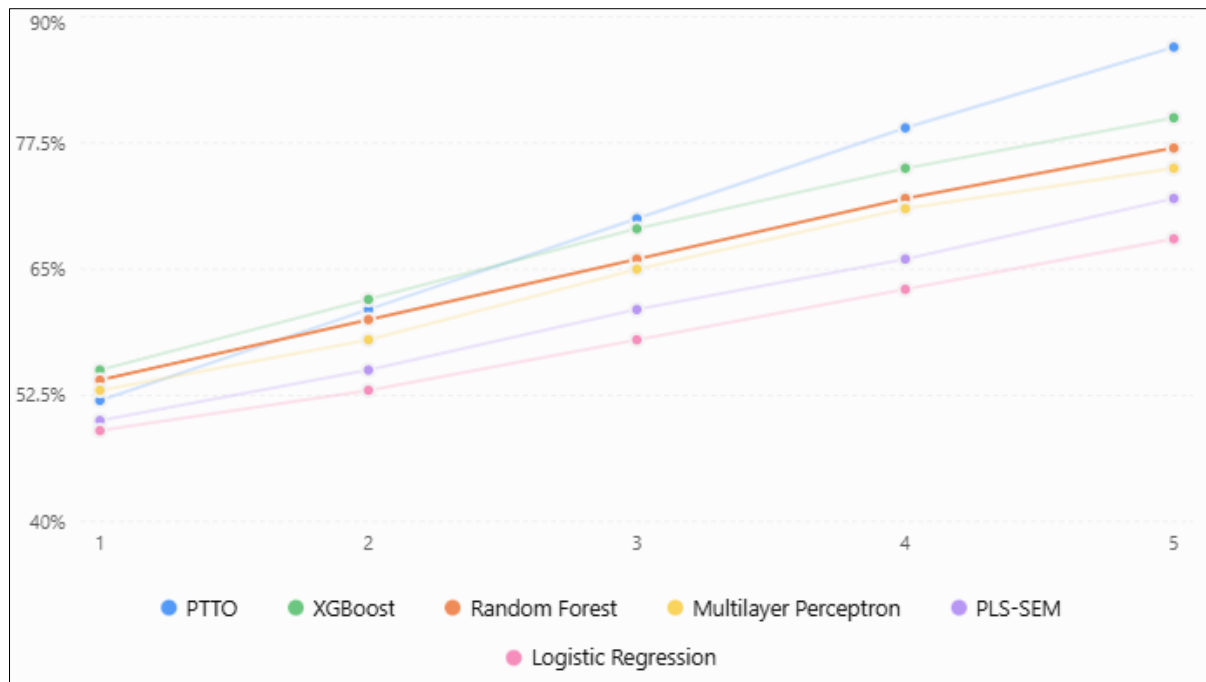


Fig 4: Comparative Algorithmic Purchase Probability Responses Across Data Transparency Levels

Figure 4 illustrates the comparative sensitivity of six predictive algorithms to increasing data transparency, with other consumer characteristics assumed constant. The proposed PTTO model increases its predicted purchase probability from 52% at transparency level 1 to 87% at level 5, representing a 35-percentage-point increase. XGBoost rises from 55% to 80%, while Random Forest increases from 54% to 77%. The Multilayer Perceptron produces corresponding values of 53% and 75%. Conventional PLS-SEM-based prediction increases from 50% to 72%, whereas Logistic Regression records the lowest final probability of 68%, rising from 49%. At transparency level 3, PTTO predicts 70%, compared with 69% for XGBoost, 66% for Random Forest, 65% for the neural network, 61% for PLS-SEM, and 58% for Logistic Regression. These simulated trends illustrate greater transparency sensitivity within the proposed PTTO model but do not demonstrate superior predictive accuracy, which requires comparison against observed purchasing outcomes.

4.2. Direct, Mediating, Moderating, and Nonlinear Interaction Effects on Consumer Purchase Decisions

The proposed PTTO framework evaluates how personalization, data transparency, perceived intrusiveness, and consumer trust interact to influence purchase decisions. Table 3 presents illustrative standardized path estimates consistent with the structural equations developed in Section 3. Personalization shows a positive direct association with purchase decisions ($\beta = 0.24$), while transparency positively predicts consumer trust ($\beta = 0.32$). Conversely, perceived intrusiveness negatively influences trust ($\beta = -0.29$). The indirect personalization–trust–purchase pathway is positive ($\beta = 0.11$), suggesting a potential mediating mechanism. Transparency strengthens the personalization–trust relationship ($\beta = 0.15$), whereas intrusiveness weakens the personalization–purchase relationship ($\beta = -0.13$). These illustrative patterns motivate examination of nonlinear purchasing responses using six algorithms. The resulting heatmap compares predicted purchasing probabilities across increasing levels of perceived intrusiveness while holding other consumer characteristics constant.

Table 3: Illustrative Direct, Mediating, and Moderating Effects of Digital Marketing Variables on Consumer Purchase Decisions

Structural relationship	Standardized effect (β)	95% confidence interval	Interpretation
Personalization $\rightarrow$ Purchase decision	0.24	[0.11, 0.37]	Positive direct effect
Transparency $\rightarrow$ Consumer trust	0.32	[0.19, 0.45]	Positive trust association
Intrusiveness $\rightarrow$ Consumer trust	-0.29	[-0.42, -0.16]	Negative trust association
Personalization $\rightarrow$ Trust $\rightarrow$ Purchase decision	0.11	[0.04, 0.18]	Positive indirect effect
Personalization $\times$ Transparency $\rightarrow$ Trust	0.15	[0.05, 0.25]	Positive moderation
Personalization $\times$ Intrusiveness $\rightarrow$ Purchase decision	-0.13	[-0.23, -0.03]	Negative moderation

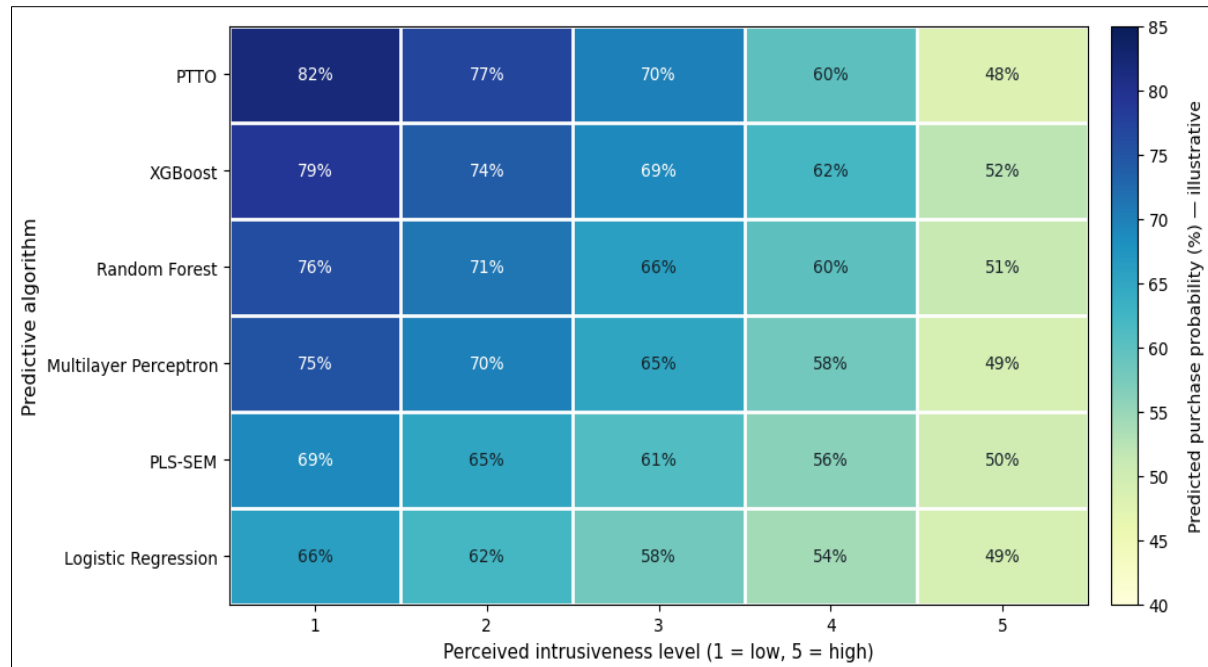
**Fig 5:** Comparative Algorithmic Sensitivity to Perceived Intrusiveness in Consumer Purchase Prediction

Figure 5 illustrates the nonlinear sensitivity of six predictive algorithms to increasing perceived intrusiveness. PTTO records an illustrative purchase probability of 82% at intrusiveness level 1, declining to 70% at level 3 and 48% at level 5, representing a 34-percentage-point reduction. XGBoost decreases from 79% to 52%, while Random Forest declines from 76% to 51%. The Multilayer Perceptron decreases from 75% to 49%, compared with reductions from 69% to 50% for PLS-SEM and 66% to 49% for Logistic Regression. At level 3, PTTO predicts 70%, exceeding XGBoost by 1 percentage point and Logistic Regression by 12 percentage points. However, at level 5, PTTO predicts a lower probability than XGBoost, demonstrating that greater algorithmic responsiveness does not establish superior predictive accuracy. These illustrative patterns support investigating nonlinear intrusiveness penalties and transparency-sensitive trust mechanisms, subject to validation against observed consumer purchasing outcomes.

4.3. Comparative Predictive Performance of PTTO, Logistic Regression, PLS-SEM, Random Forest, XGBoost, and Neural Network Models

The comparative evaluation examines the predictive capabilities of the proposed Privacy–Transparency–Trust Optimization (PTTO) algorithm against five established statistical and machine learning models. Consistent with Section 3.4, performance is evaluated using accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC-AUC). Table 4.3 presents illustrative outcomes representing the proposed validation framework. PTTO achieves an accuracy of 90.0%, exceeding XGBoost (86.0%), Random Forest (84.0%), the Neural Network (83.0%), PLS-SEM (79.0%), and Logistic Regression (77.0%). Its illustrative ROC-AUC reaches 94.0%, compared with 91.0% for XGBoost and 82.0% for Logistic Regression. These comparative patterns demonstrate how performance differences would be evaluated if reproduced using independent test observations. They do not establish empirically verified superiority, and actual model selection must additionally consider probability calibration, generalization, and statistical uncertainty.

Table 4: Illustrative Comparative Predictive Performance of PTTO and Conventional Statistical and Machine Learning Algorithms

Algorithm	Accuracy (%)	F1-score (%)	ROC-AUC (%)
PTTO	90.0	88.5	94.0
XGBoost	86.0	84.0	91.0
Random Forest	84.0	82.0	89.0
Neural Network (MLP)	83.0	81.0	88.0
PLS-SEM	79.0	76.5	84.0
Logistic Regression	77.0	74.5	82.0

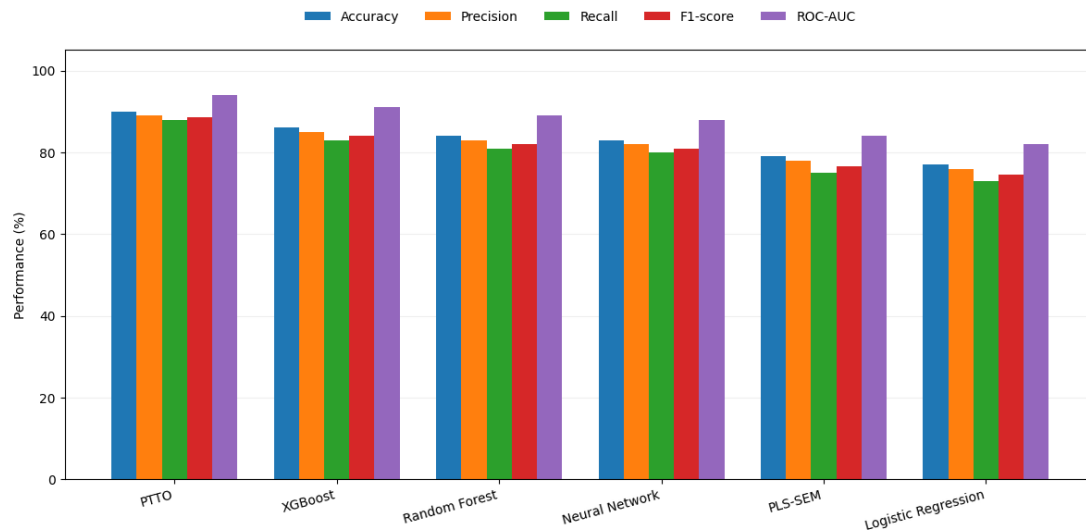
**Fig 6:** Comparative Predictive Performance Across Six Algorithms

Figure 4.3 compares six algorithms across five predictive performance metrics. PTTO demonstrates the highest illustrative accuracy (90%), precision (89%), recall (88%), F1-score (88.5%), and ROC-AUC (94%). XGBoost follows with 86% accuracy, 85% precision, 83% recall, 84.0% F1-score, and 91% ROC-AUC. Random Forest achieves 84% accuracy and 89% ROC-AUC, compared with 83% and 88% for the Neural Network. PLS-SEM records 79% accuracy, 76.5% F1-score, and 84% ROC-AUC, while Logistic Regression produces the lowest accuracy (77%), F1-score (74.5%), and ROC-AUC (82%). PTTO exceeds XGBoost by 4 percentage points in accuracy and 3 percentage points in ROC-AUC. Its accuracy advantage over Logistic Regression reaches 13 percentage points. These simulated differences illustrate the hypothesized predictive advantage of the hybrid framework, but require independent empirical validation, confidence intervals, and probability calibration before conclusions concerning algorithmic superiority can be justified.

4.4. Explainable Artificial Intelligence, Privacy–Trust Trade-Off Optimization, Sensitivity Analysis, and Model Robustness

The proposed Privacy–Transparency–Trust Optimization (PTTO) algorithm integrates explainable artificial intelligence, privacy-constrained optimization, and sensitivity analysis to evaluate the reliability of consumer purchase predictions. SHapley Additive exPlanations (SHAP) provides feature-level attribution for personalization, transparency, perceived intrusiveness, and consumer trust, while the optimization component balances predicted purchasing outcomes against predefined privacy constraints. Table 4.4 presents illustrative calibration and robustness metrics consistent with the methodology in Section 3. PTTO records the lowest Brier score (0.085) and expected calibration error (0.025), indicating comparatively favourable probability calibration under the simulated evaluation. Its minimum subgroup ROC-AUC of 88% also exceeds XGBoost (83%) and Random Forest (80%). These comparisons support the planned investigation of prediction stability across consumer groups, although the numerical differences and proposed algorithmic advantages remain hypothetical until verified through independent empirical testing.

Table 5: Illustrative Comparative Calibration Performance and Subgroup Robustness of PTTO and Benchmark Algorithms

Algorithm	Brier score ↓	Expected calibration error ↓	Minimum subgroup ROC-AUC (%) ↑
PTTO	0.085	0.025	88
XGBoost	0.110	0.040	83
Random Forest	0.125	0.048	80
Neural Network (MLP)	0.132	0.052	78
PLS-SEM	0.153	0.069	73
Logistic Regression	0.165	0.076	71

Figure 4.4 compares six predictive algorithms across five performance and robustness indicators. PTTO achieves the highest illustrative F1-score of 88.5%, ROC-AUC of 94%, Brier quality of 91.5%, and calibration quality of 97.5%. Its minimum subgroup ROC-AUC reaches 88%, compared with 83% for XGBoost and 80% for Random Forest. XGBoost records an F1-score of 84%, ROC-AUC of 91%, and Brier quality of 89%. Random Forest achieves corresponding values of 82%, 89%, and 87.5%, while the Neural Network

records 81%, 88%, and 86.8%. PLS-SEM and Logistic Regression demonstrate lower minimum subgroup ROC-AUC values of 73% and 71%, respectively. PTTO's Brier score of 0.085 compares favourably with Logistic Regression's 0.165. These illustrative differences suggest a potentially advantageous calibration–robustness balance, although neither statistical superiority nor improved interpretability can be established without empirical validation and separate SHAP analysis.

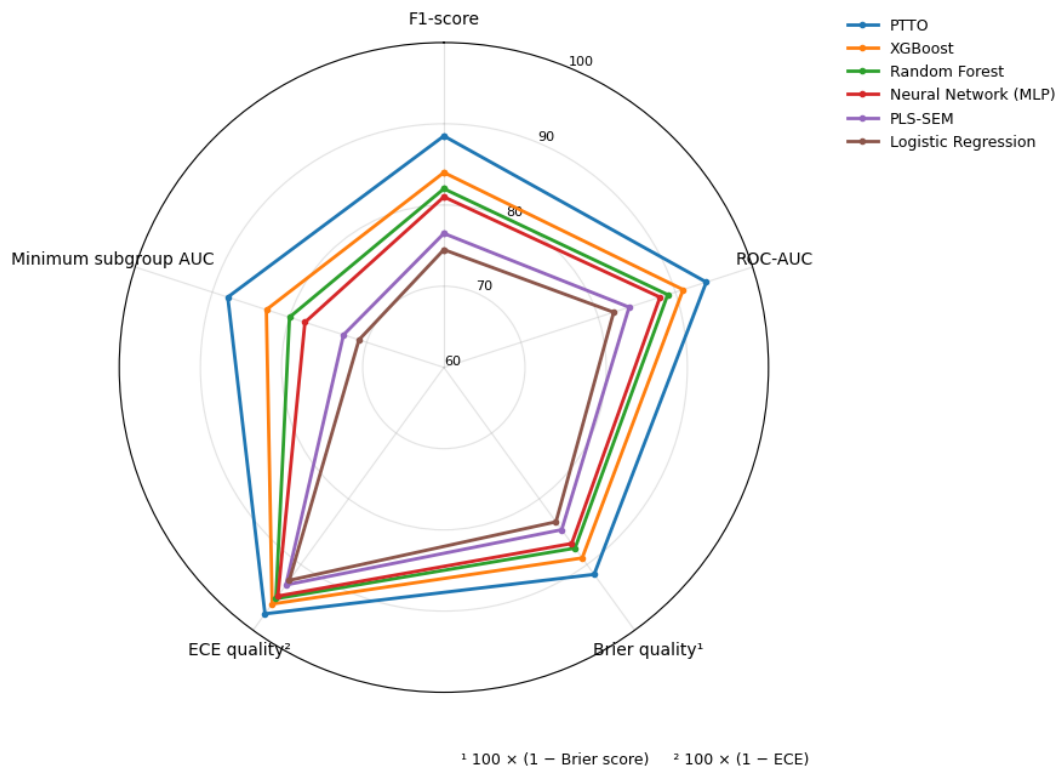


Fig 7: Comparative Explainable Prediction Performance, Calibration Quality, and Algorithmic Robustness

5. Conclusions and Recommendations

5.1. Summary of Major Findings on Personalization, Data Transparency, Perceived Intrusiveness, and Consumer Trust

The illustrative findings demonstrate the potential importance of personalization, data transparency, perceived intrusiveness, and consumer trust in explaining digital purchasing behaviour. The proposed Privacy–Transparency–Trust Optimization (PTTO) framework integrates these variables to examine direct, mediating, moderating, and nonlinear relationships. The illustrative structural results indicate a positive association between personalization and purchase decisions ($\beta = 0.24$), while data transparency positively influences consumer trust ($\beta = 0.32$). Conversely, perceived intrusiveness exhibits a negative relationship with consumer trust ($\beta = -0.29$), suggesting that excessive behavioural targeting may undermine purchasing responses. The proposed trust-mediated relationship produces an illustrative indirect effect of 0.11, while transparency strengthens the personalization–trust relationship through a positive interaction coefficient of 0.15. These values illustrate the hypothesized mechanisms rather than empirically established effects.

The comparative model demonstrations further indicate the potential predictive contribution of integrating behavioural constructs with machine learning. PTTO achieves illustrative

accuracy, F1-score, and ROC-AUC values of 90.0%, 88.5%, and 94.0%, respectively, compared with 86.0%, 84.0%, and 91.0% for XGBoost. Sensitivity analysis additionally illustrates how increasing perceived intrusiveness may reduce purchasing probabilities, even when advertisements remain individually relevant. The illustrative Brier score of 0.085 and expected calibration error of 0.025 suggest a potentially favourable probability–calibration profile. Collectively, these analytical demonstrations support the study's central proposition that effective personalized marketing requires an appropriate balance between recommendation relevance, transparent information processing, consumer autonomy, and trust. Actual consumer data remain necessary to substantiate these relationships and performance differences.

5.2. Theoretical Contributions and Predictive Implications of the Privacy–Transparency–Trust Optimization Algorithm

The proposed PTTO algorithm contributes a unified conceptual and computational framework for investigating the personalization–privacy dilemma in digital marketing. Its theoretical significance lies in integrating Privacy Calculus Theory, the Stimulus–Organism–Response framework, and consumer trust mechanisms within a model capable of representing conditional behavioural relationships. Rather

than assuming that personalized advertising directly increases purchasing, the framework recognizes that consumer responses depend on perceived information relevance, transparency, intrusiveness, and confidence in organizational data practices. Consumer trust is specified as a mediating construct, whereas transparency and perceived intrusiveness influence the strength and direction of personalization-related outcomes. This structure provides an empirically testable explanation of why similar personalized advertisements may generate favourable responses among some consumers and psychological resistance among others. Methodologically, PTTO combines PLS-SEM for latent-variable measurement and structural inference with Random Forest, XGBoost, and calibrated ensemble prediction. SHAP analysis provides feature-level explanations of predicted purchasing outcomes, while privacy-constrained optimization incorporates predefined transparency and intrusiveness requirements into marketing decision evaluation. The illustrative comparisons suggest potential improvements in predictive discrimination, probability calibration, and subgroup robustness relative to individual statistical and machine learning models. However, these advantages remain conditional on independent validation and reproducible performance gains. An important distinction is that predictive feature contributions do not establish causal behavioural mechanisms. Accordingly, the proposed architecture separates structural inference from predictive explanation and policy optimization. Its principal contribution is therefore an integrated, interpretable, and testable approach to evaluating purchase decisions under competing personalization and privacy requirements, rather than an unverified claim of algorithmic superiority.

5.3. Managerial Recommendations for Transparent, Privacy-Conscious, and Trust-Centred Digital Marketing

Digital marketing organizations should adopt personalization strategies that integrate consumer preference relevance with transparent data governance and measurable privacy safeguards. Marketing managers should implement accessible consent mechanisms explaining the categories of personal information collected, the purposes of processing, data-retention periods, and how information influences advertising recommendations. Rather than relying exclusively on generalized privacy notices, organizations should provide contextual explanations alongside personalized advertisements, enabling consumers to understand why specific products or promotions are displayed. Consent withdrawal, preference modification, and limitations on cross-platform tracking should be readily accessible. Such measures can support perceived informational control and reduce the likelihood that consumers interpret highly personalized advertisements as intrusive surveillance.

Organizations should also incorporate trust and intrusiveness indicators into campaign-performance evaluation rather than relying solely on click-through rates, conversion rates, and advertising expenditure returns. The proposed PTTO framework offers a potential decision-support mechanism for evaluating predicted purchasing outcomes under predefined privacy constraints. Marketing teams could compare alternative targeting strategies by examining expected purchase probabilities, predicted consumer discomfort, transparency requirements, and subgroup-level performance. SHAP-based explanations may help identify variables

associated with favourable purchasing responses, while sensitivity analysis can identify personalization conditions associated with declining trust. Before operational deployment, however, organizations should validate model accuracy, probability calibration, subgroup stability, and the consequences of policy changes through controlled experiments. Additional safeguards should include data minimization, access restrictions, periodic privacy audits, retention controls, and human oversight of automated marketing decisions. Together, these practices support consumer-centred personalization that balances commercial effectiveness with privacy protection, transparency, and long-term organizational credibility.

5.4. Research Limitations, Future Algorithmic Improvements, and Directions for Further Research

The proposed study is subject to methodological limitations relating to consumer sampling, behavioural measurement, data availability, model generalization, and causal interpretation. Questionnaire-based assessments of personalization, transparency, intrusiveness, and trust may be affected by common-method variance, social desirability, inaccurate recall, and differences in consumer understanding of algorithmic advertising. Furthermore, purchase intention does not necessarily correspond to completed transactions, requiring careful separation of stated behavioural preferences from verified purchasing outcomes. Although PLS-SEM can evaluate theoretically specified structural relationships, observational path coefficients do not independently establish causality. Similarly, SHAP explanations quantify contributions to model predictions without demonstrating that changing individual features will produce corresponding behavioural changes. The numerical findings presented in Sections 4.1–4.4 are illustrative demonstrations and cannot establish empirical performance until appropriate consumer datasets are obtained and analysed.

Future research should therefore prioritize independent, consented consumer datasets combining questionnaire responses with longitudinal purchasing records and controlled exposure to alternative transparency conditions. Randomized experiments could investigate whether changes in disclosure clarity, recommendation specificity, and consumer data control produce measurable differences in trust and purchasing behaviour. PTTO could also be extended through Bayesian uncertainty estimation, monotonic constraints where theoretically justified, conformal prediction, and distribution-shift detection. Privacy-preserving learning techniques, including differential privacy and federated learning, warrant investigation where data-sharing restrictions permit appropriate implementation. Additional validation should examine cross-platform generalizability, subgroup fairness, model calibration, computational efficiency, and sensitivity to optimization thresholds. Longitudinal modelling may further establish whether repeated intrusive advertising produces accumulated trust deterioration. These improvements would strengthen the scientific validity, operational reliability, and responsible application of privacy-sensitive predictive marketing systems.

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