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Does integrating personal data via CDPs improve banking responsiveness? Moderating influence of local culture

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Abstract

In the growing importance of personalized digital services in the banking sector, the integration of personal data through customer data platforms (CDPs) has become a strategic priority. This study explores how personal data privacy influences perceived personalization and operational efficiency in digital banking services, while also investigating the moderating role of local culture. The research is motivated by increasing consumer demands for both personalized services and greater control over personal data. Personal data privacy was conceptualized as a multidimensional construct comprising knowledge, experience, control, willingness to value privacy, and trust. A quantitative method using partial least squares structural equation modeling (PLS-SEM) with 10,000 bootstrapping resamples was employed. The analysis was conducted using SmartPLS version 4.1.1.4, which enables efficient estimation of complex models. Data were collected offline from 200 respondents who are active users of digital banking services from Himbara member banks. The results indicate that personal data privacy has a significant positive effect on both perceived personalization and operational efficiency. Among its dimensions, willingness to value privacy emerged as the most influential. Local culture was found to significantly moderate both relationships, suggesting that cultural context plays a critical role in shaping digital service outcomes. These findings contribute to theory and practice by highlighting the importance of integrating privacy protection and cultural sensitivity in the design of personalized digital banking services.

Introduction

The rapid advancement of digital technology has transformed financial service delivery, enabling banks to provide faster, more efficient, and personalized services through optimized customer data (Bueno et al., 2024; Kitsios et al., 2021; Rodrigues et al., 2022). A key strategy in this context is the implementation of customer data platforms (CDP), which integrate and manage customer data across channels to enhance marketing effectiveness and service quality (De Luca et al., 2021; Shah & Chase, 2025). From a consumer behavior perspective, CDP adoption is closely tied to perceptions of personal data privacy, as consumers increasingly seek personalized experiences while demanding data security, transparency, and control (Jian & Dan, 2024). Consequently, managing privacy perception is crucial for fostering trust and ensuring the success and public acceptance of digital banking systems.

Personal data management in digital banking is not merely a technological process but is deeply tied to the formation and maintenance of customer trust. According to trust theory (Doney & Canno, 1997; Mayer & Davis, 1995), trust emerges when customers perceive ability, integrity, and benevolence in the institutions handling their data. As consumers become more aware and

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critical of data usage, transparency, control, and protection assurances become crucial in strengthening trust (S. Wang et al., 2024). When customers feel knowledgeable, in control, and have positive experiences with data management, their trust in digital services increases. In this regard, a positive perception of data privacy acts as a psychological antecedent that enhances engagement and loyalty (Chen et al., 2023), while enabling banks to deliver services that are more relevant to individual preferences (Durans & Mainardes, 2025).

Effective data management leads to improved perceived personalization — the extent to which customers feel that products and services match their personal needs. By leveraging big data, predictive analytics, and artificial intelligence, banks can better understand customer behaviors, preferences, and needs, thereby offering more relevant products and communications (Famoti et al., 2025; Kona, 2020). Perceived personalization strengthens satisfaction and loyalty (Lambillotte et al., 2022; Li, 2016). Within the trust theory framework, personalization operates as an outcome of trust-based interactions — consumers are more open to data-driven personalization when they believe data is used transparently and with good intent.

However, personalization relies heavily on responsible data governance. Regulations, technological innovation, and ethical management are essential to balancing service optimization and privacy protection (Gil et al., 2025; Spiekermann et al., 2015). Hence, customer perceptions of privacy affect not only their trust level but also their perceived service quality (Durans & Mainardes, 2025; E. S. T. Wang & Lin, 2017). The relationship between data privacy and perceived personalization highlights a strategic intersection where privacy reliability aligns with perceived service value.

Digitalization also enhances operational efficiency within financial institutions (Bueno et al., 2024). Studies indicate that data integration accelerates transactions, reduces manual workloads, and improves procedural efficiency (Kumar et al., 2023; Luo et al., 2022). However, this efficiency is achievable only when customers willingly share data under the belief that it is managed securely. Positive perceptions of data protection serve as a critical enabler of digital optimization (Martínez-Navalón et al., 2023). When customers feel secure, operational processes become smoother and more effective, indicating that trust, data security, and technological reliability form the foundation of successful digital transformation.

In the Indonesian context, particularly in eastern regions such as Maluku, cultural factors critically shape privacy perception and institutional trust. Drawing on Hofstede's framework, Maluku society is characterized by collectivism, high power distance, and strong interpersonal trust, which influence how individuals evaluate privacy and institutional reliability. Collectivist values prioritize group harmony, relational obligation, and interpersonal closeness in decision-making (Tjosvold et al., 2003), leading consumers to rely on relational assurance and interpersonal interactions rather than impersonal technological cues. In banking, this manifests as preferences for face-to-face interactions and trust in familiar local representatives (Masriat et al., 2024; Wakano, 2019), reflecting Hofstede's notion that cultural values shape uncertainty avoidance and trust formation, embedding privacy perception and technology adoption within social relationships rather than individual cognition.

Such cultural mechanisms indicate that personalization and efficiency in digital banking are not purely technological phenomena but socially embedded trust processes. Customers in collectivist and high-trust societies interpret privacy assurances not merely as regulatory compliance but as expressions of respect for communal norms and relational integrity. When banks demonstrate transparency and accountability in managing personal data, users perceive these actions as culturally respectful, reinforcing trust and engagement. Thus, Maluku's local culture represents an empirical manifestation of Hofstede's collectivism and power distance, offering a conceptual model relevant to broader Asian contexts (AbdulKareem & Oladimeji, 2024; Dhagarra et al., 2020; Oesterreich et al., 2024).

Nevertheless, previous studies have largely focused on the technical or organizational implementation of CDPs while neglecting how local culture interacts with privacy perceptions and personalization in shaping digital service adoption. Moreover, CDP constructs are often analyzed from managerial perspectives rather than consumer trust viewpoints, despite end users being the primary data providers. The interrelation between privacy perception, perceived personalization, and operational efficiency has rarely been examined within an integrated model. Furthermore, the moderating role of local culture remains underexplored, particularly in Indonesia's banking sector.

This study investigates the impact of personal data privacy perception on perceived personalization and operational efficiency in digital banking, with local culture as a moderating factor based on Hofstede's framework. Using an exploratory approach, it examines how privacy dimensions—knowledge, experience, control, concern, and trust—affect consumer acceptance of personalized and efficient digital services, and how cultural orientation amplifies or attenuates these effects among Himbara bank customers undergoing digital transformation. Theoretically, the study advances digital trust and CDP literature by integrating trust theory and Hofstede's cultural framework into a consumer-centered model, while practically providing insights for banks to develop culturally sensitive privacy strategies and socially grounded digital experiences. Emphasizing data protection, personalization, and efficiency alongside cultural understanding is essential for inclusive and sustainable financial innovation in Indonesia.

Literature Review and Hypotheses Development

Personal data privacy, perceived personalization, and operational efficiency

The rapid development of digital technology has prompted the strategic adoption of customer data platforms (CDPs) to integrate customer data, enabling personalized services, marketing automation, and enhanced customer loyalty and revenue (Blömker & Albrecht, 2025; Jian & Dan, 2024). However, while prior studies highlight the operational advantages of CDPs, there is limited understanding of how consumer perceptions of personal data privacy critically shape these benefits. Personal data privacy reflects not only the technical protection of information but also the trust consumers place in banks regarding the ethical collection, use, and security of their data (Durans & Mainardes, 2025; S. Wang et al., 2024). This duality suggests that CDP effectiveness is contingent upon both technological integration and the social-psychological acceptance of privacy practices, a nuance often overlooked in the literature.

Extending this notion, Ioannou et al. (2020) conceptualize personal data privacy as comprising seven dimensions: knowledge, experience, control, willingness to value privacy, trust, awareness, and protection regulation. Yet, subsequent studies, such as Durans and Mainardes (2025), have focused only on five dimensions, excluding awareness and protection regulation, arguing that these are more influenced by social or international regulatory contexts than by individual perception. This divergence indicates a potential gap in understanding which dimensions are most relevant for predicting consumer behavior, highlighting the need for a more focused approach in operationalizing privacy perception for digital banking contexts.

Marketing personalization represents the practical outcome of effectively managing personal data, enabling banks to tailor services, communication, and offerings to individual preferences (Afifah & Putri, 2023). Nevertheless, the literature shows mixed evidence regarding the mechanisms linking data privacy to perceived personalization. While Tran et al. (2020) argue that perceived personalization depends on ethical and transparent data use, some studies suggest that high privacy concerns can paradoxically reduce consumers' willingness to engage with personalized services despite adequate data protection (Shin et al., 2025; Van Buggenhout et al., 2023). Such contradictions underscore the importance of examining how privacy perception mediates the relationship between data collection practices and personalization outcomes, rather than assuming a uniformly positive effect.

Operational efficiency in digital banking is similarly contingent on customer engagement with privacy practices. C.V. and Agrawal (2024) define operational efficiency as the optimal management of business processes to reduce waste, cost, and time, while in digital banking, technology-driven processes enhance transaction speed, accuracy, and service automation (Bueno et al., 2024; Handoyo et al., 2023). Nevertheless, efficiency gains are constrained by the extent to which customers voluntarily share their personal data and trust the bank's data management. Evidence from Iman (2024), Juma'h and Alnsour (2019), and Schäfer et al. (2023) indicates that inadequate privacy management or data breaches can significantly impair operational performance and profitability, revealing a clear dependency of operational efficiency on consumer trust and privacy perceptions.

Overall, the literature collectively suggests that personal data privacy serves as a critical determinant of both perceived personalization and operational efficiency. Positive perceptions of data protection not only foster consumer feelings of safety and value (Shin et al., 2025; Van Buggenhout et al., 2023; Zhang et al., 2025) but also enhance willingness to participate in data-driven processes that underlie operational efficiency. These synthesized insights form the theoretical rationale for the following hypotheses:

H_1: Personal data privacy has a positive effect on perceived personalization.

H_2: Personal data privacy has a positive effect on the operational efficiency of digital services.

Moderating local culture

Despite these insights, prior studies rarely account for socio-cultural variations that may modulate the effect of personal data privacy on service outcomes. Local culture embodies shared values, norms, and social preferences that influence how individuals interact with technology and evaluate institutions (Blegur & Dyah, 2021). In eastern Indonesia, particularly Maluku, cultural traits such as collectivism, strong interpersonal trust, and preference for face-to-face interaction may shape both willingness to share personal data and receptivity to personalized services (Javaid et al., 2024). Such cultural tendencies can either reinforce or attenuate the positive relationship between privacy perception and perceived personalization, indicating the necessity of integrating culture as a moderating construct.

Empirical evidence across organizational and service contexts further supports this moderating role. Studies by Escandon et al. (2023), Kagaari (2011), and Oyuga et al. (2025) demonstrate that cultural factors can significantly influence operational efficiency, productivity, and the effectiveness of strategic initiatives. By extension, in digital banking, local culture may similarly strengthen or weaken the impact of personal data privacy on both perceived personalization and operational efficiency. Accordingly, the following hypotheses are proposed:

H_{3a}: Local culture moderates the influence of personal data privacy on perceived personalization among digital bank users.

H_{3b}: Local culture moderates the influence of personal data privacy on the operational efficiency of digital bank services.

Research Methods

Sample and data collection

This research is an explanatory study aimed at examining the causal relationship between personal data privacy perception and perceived personalization and operational efficiency, while considering the moderating role of local culture. To capture potential differences in perceptions shaped by cultural backgrounds, the study specifically targeted respondents from Maluku. Data were collected across four representative regions, namely Ambon City, Tual City, Central Maluku Regency, and Buru Regency. This geographic distribution ensures that respondents reflect the local cultural context pertinent to collectivism and power distance, as conceptualized in Hofstede's framework, and allows for a meaningful examination of local culture as a moderating variable.

The sampling technique employed was purposive sampling, with inclusion criteria requiring respondents to be active customers of one of the Himbara banks—Bank Mandiri, BRI, BNI, and BTN—and to have used digital banking services. To maintain a balanced representation across banks, 60 respondents were targeted per bank, resulting in a total of 240 respondents. After screening for completeness, 200 respondents fully completed the questionnaire, yielding a response rate of 83.33%. Referring to Roscoe (1975), a sample size of 30–500 is considered adequate for social science research, indicating that the 200 valid responses used in this study are sufficient to support the complexity of the PLS-SEM model and provide reliable statistical estimates.

Data collection was conducted offline using printed questionnaires distributed directly to respondents. The questionnaire included two sections: demographic information (gender, age, and occupation) and measurement items for the research variables. Personal data privacy served as an exogenous variable measured as a reflective-reflective construct with five dimensions: knowledge, experience, control, willingness, and trust in personal data management. Perceived personalization and operational efficiency were treated as endogenous variables, representing respondents' perceptions of service suitability and operational efficiency resulting from digital banking. Local culture acted as a moderating variable, hypothesized to influence the strength of the relationships between these endogenous variables. All items were measured on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Given the complexity of the constructs, including high-level reflective constructs and moderation effects, data analysis was conducted using SmartPLS version 4.1.1.4. This version allows advanced construct estimation without the need to export latent variable scores to a separate data file (Cheah et al., 2024). To test the significance of the relationships, a bootstrapping procedure with 10,000 subsamples was employed, providing stable estimates and accurate assessment of model validity and reliability, particularly for models including moderation interactions (Sarstedt et al., 2022).

By explicitly grounding the study in these four regions and justifying the sample size, this research ensures that the moderating role of local culture is both conceptually and empirically supported, allowing for a robust investigation of how collectivist values and power distance influence the interplay between privacy perception, personalization, and operational efficiency in digital banking services.

Operational definitions and variable measurement

First, personal data privacy is an individual's perception of the extent to which they understand, have experience with, feel in control of, care about, and trust the bank's management of personal data. This variable encompasses five main dimensions: knowledge of personal data privacy, experience in personal data privacy, control over personal data, willingness to value the privacy of personal data, and trust in sharing personal data information.

The knowledge of personal data privacy dimension reflects the level of individual understanding regarding the processes of collecting, using, and accessing their personal data, which is measured through three indicators: understanding, knowing, and being aware. Experience in personal data privacy refers to individuals' perceptions of their experience in obtaining protection for their personal data while using bank services, as indicated by the indicators of experiencing, protecting, and maintaining. Next, control over personal data measures the extent to which individuals feel they can regulate, choose, and manage the personal information they provide to the bank. Meanwhile, willingness to value the privacy of personal data indicates individuals' concern and awareness of the importance of maintaining the security of personal data, represented by the indicators of paying attention to, considering, and being vigilant about. Finally, trust in sharing personal data information reflects individuals' belief that banks will manage personal data securely and responsibly, with indicators including providing, trusting, protecting, and guaranteeing (Durans & Mainardes, 2025; Ioannou et al., 2020).

Second, perceived personalization refers to an individual's subjective perception of the extent to which services, products, or information delivered by a service provider are considered appropriate and relevant to their personal characteristics, needs, and preferences. This variable is measured through five main indicators: receiving (information tailored to needs), providing (individualized offers), adapting (adjusting to personal conditions), treating (special treatment as a customer), and trusting (confidence in the personalization received) (Tran et al., 2020).

Third, operational efficiency reflects customer perceptions of the performance of digital banking services in terms of speed, simplification, and improved quality of service processes. This efficiency is achieved through easier access, minimal manual labor, increased comfort, and a continuously improving work system. This variable is measured through five key indicators: accelerating, regulating, accessing, reducing, and improving (C.V. & Agrawal, 2024).

Fourth, local culture refers to a set of values, norms, and social practices that shape people's preferences in interacting and receiving services, including digital banking services. In regions that highly value social relationships, such as eastern Indonesia, local culture plays a crucial role in shaping community comfort and trust in technology-based services, particularly through personal interaction and social proximity with service providers. Therefore, this variable is measured through three indicators: building, recognizing, and trusting (Raja et al., 2024; Rasoolimanesh et al., 2021). The questionnaire items are shown in Table 1.

Table 1. Questionnaire Items

Construct	Indicator	Themes	Sources
Knowledge of Personal Data Privacy (KP)	KP1	I clearly understand how the bank uses my personal data.	(Durans & Mainardes, 2025; Ioannou et al., 2020)
	KP2	I am well aware of the extent to which my personal information can be accessed by other parties through the bank.	
	KP3	I know that the bank needs to obtain my permission before collecting my personal data.	
Experience in Personal Data Privacy (EP)	EP1	I have never experienced any issues with my personal data while using bank services.	
	EP2	So far, I have always felt that my personal data is protected and has never been misused by others.	
	EP3	I am confident that the bank always keeps my data safe and does not share it with others without my permission.	
Control Over Personal Data (CO)	CO1	I feel I have full control over who can access my personal data stored by the bank.	
	CO2	I can clearly choose which personal data the bank can share.	
	CO3	I clearly understand how the bank uses my personal data.	
	CO4	I am confident that I can manage and control my personal data provided to the bank myself.	
Willingnes to Value The Privacy of Personal Data (WV)	WV1	I pay close attention to how the bank manages my personal data.	
	WV2	I consider maintaining the security of personal data to be very important.	
	WV3	I am always vigilant about the potential for personal data leaks from the bank.	
Trust to Sharing Personal Data Information (TS)	TS1	I feel comfortable providing personal data to the bank because I am confident that the data will be protected.	
	TS2	I believe that the bank can keep my personal data confidential.	
	TS3	I am confident that the bank has a system capable of securely protecting customers' personal information.	
	TS4	I believe that the bank guarantees the security and protection of each customer's personal data.	
Perceived Personalization (PP)	PP1	The information or offers I received from the bank are in line with my personal needs. Make it. I feel the bank is offering me a specifically tailored offer.	(Tran et al., 2020)
	PP2	Overall, the bank's services and promotions are suitable for my current situation and conditions.	
	PP3	I feel treated as a special customer because the service provided feels personalized.	
	PP4	I believe that the information or promotions from the bank have been tailored to my habits and needs.	
	PP5	The use of digital systems makes banking services faster and more efficient.	
Operational Efficiency (OE)	OE1	Queues and wait times are shorter because the service process is better organized.	(C.V. & Agrawal, 2024)
	OE2	I can access bank services anytime, so my needs are met faster.	
	OE3	Digital technology in banks helps reduce manual processes and improve service convenience.	
	OE4	The bank continues to improve its operations so that customer service gets better over time.	
	OE5	I find that the people around me are generally friendly and enjoy building good relationships.	

Construct	Indicator Themes		Sources
Local Culture (LC)	LC1	I feel it's important to get to know someone in person before trusting them or using their services, including banking services.	(Raja et al., 2024; Rasoolimanesh et al., 2021)
	LC2	I am more comfortable receiving service from bank tellers I have met or known before.	
	LC3	The information or offers I received from the bank are in line with my personal needs. Make it. I feel the bank is offering me a specifically tailored offer.	

Source: Data processing, 2025

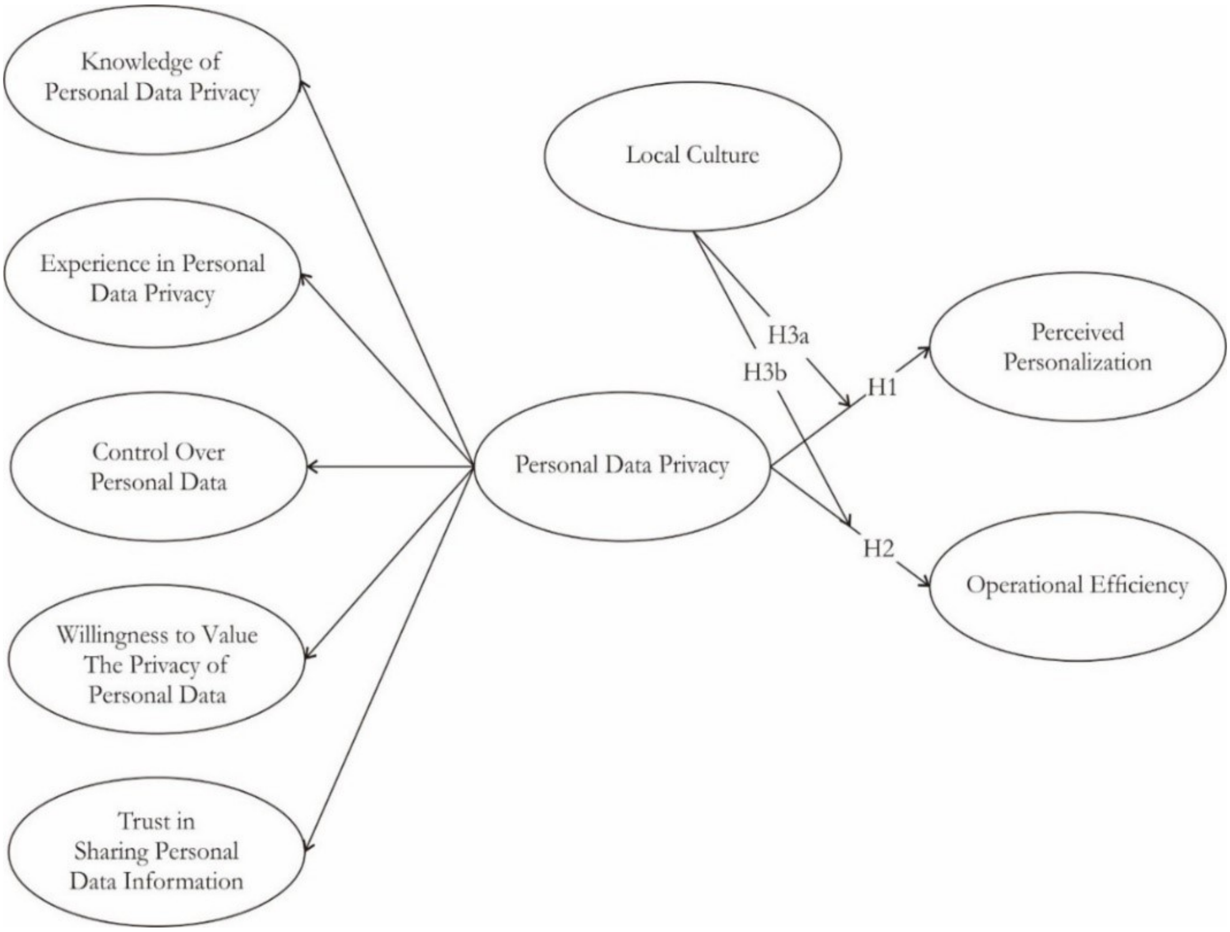

Figure 1. Research Framework
Source: Authors conceptualization

Results and Discussion

Respondent profile

A total of 200 respondents who participated in this study were active customers of digital services from Himbara banks. The respondents were distributed across four representative areas in Maluku, with a larger proportion from Ambon City (60; 30%), followed by Central Maluku Regency (55; 27.5%), Tual City (50; 25%), and Buru Regency (35; 17.5%). Based on gender, the majority of respondents were female (133; 66.5%), while 67 respondents were male (33.5%). In terms of age, the majority of respondents were in the 20–29 age group (80; 40%), followed by the 30–39 age group (67; 33.5%), the 40–49 age group (25; 12.5%), respondents under 20 years old (21; 10.5%), and those aged 50 and above (7; 3.5%). Based on occupation, the respondents consisted of students (32; 16%), private/state-owned enterprise employees (55; 27.5%), civil servants (70; 35%), and entrepreneurs (43; 21%). This composition demonstrates the diversity of respondents' geographic and demographic backgrounds, enabling a more representative analysis of perceptions regarding the use of digital banking services in the study area.

Evaluation of the measurement model

The measurement model in this study was validated through comprehensive assessments of construct reliability, convergent validity, and discriminant validity. Construct reliability, measured using rho_a values ranging from 0.804 to 0.910 (Table 2), exceeded the minimum threshold of 0.70 (Shela et al., 2023), confirming strong internal consistency. Factor loadings for all indicators surpassed 0.70 (Hair et al., 2017), indicating that each item reliably represented its latent construct—for example, knowledge of personal data privacy (0.844–0.854) and operational efficiency (0.853–0.870) demonstrated high indicator reliability. Moreover, all average variance extracted (AVE) values ranged between 0.716 and 0.748, surpassing the 0.50 criterion (Sarstedt et al., 2022), which indicates that a substantial proportion of variance in the indicators was explained by their respective constructs, thus confirming convergent validity.

Discriminant validity was further verified using the Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker criterion (Al-khadher et al., 2024; Benitez et al., 2020). All HTMT values were below 0.85 (Table 3), and the square root of each construct's AVE exceeded its inter-construct correlations (Table 4), confirming that the constructs are empirically distinct. These combined results demonstrate that the measurement model meets the statistical standards for reliability and validity. The consistency of rho_a, high indicator loadings, satisfactory AVE scores, and clear discriminant validity collectively ensure that the constructs are robustly measured and appropriate for subsequent structural model analysis.

Table 2. Validity and Reliability

Constructs	Items	Loadings	Composite Reliability (rho_a)	Average Variance Extracted (AVE)
Knowledge of Personal Data Privacy	KP1	0.844	0.804	0.718
	KP2	0.844		
	KP3	0.854		
Experience in Personal Data Privacy	EP1	0.840	0.836	0.748
	EP2	0.885		
	EP3	0.869		
Control Over Personal Data	CO1	0.850	0.889	0.746
	CO2	0.851		
	CO3	0.869		
	CO4	0.885		
Willingnes to Value The Privacy of Personal Data	WV1	0.862	0.831	0.748
	WV2	0.840		
	WV3	0.890		
Trust to Sharing Personal Data Information	TS1	0.868	0.889	0.748
	TS2	0.848		
	TS3	0.861		
	TS4	0.882		
Perceived Personalization	PP1	0.840	0.901	0.716
	PP2	0.866		
	PP3	0.831		
	PP4	0.859		
	PP5	0.833		
Operational Efficiency	OE1	0.870	0.910	0.735
	OE2	0.853		
	OE3	0.854		
	OE4	0.853		
	OE5	0.855		
Local Culture	LC1	0.830	0.824	0.732
	LC2	0.879		
	LC3	0.857		

Source: Smart-PLS 4.1.1.4 Output, 2025

Table 3. Heterotrait-Monotrait (HTMT) Ratio

	CO	EP	KP	LC	OE	PP	TS	WV
CO								
EP	0.595							
KP	0.611	0.684						
LC	0.348	0.168	0.258					
OE	0.512	0.530	0.609	0.546				
PP	0.540	0.663	0.537	0.581	0.700			
TS	0.689	0.709	0.574	0.379	0.618	0.604		
WV	0.728	0.728	0.708	0.439	0.604	0.556	0.879	

Note. CO: Control Over Personal Data; EP: Experience in Personal Data Privacy; KP: Knowledge of Personal Data Privacy; LC: Local Culture; OE: Operational Efficiency; PP: Perceived Personalization; TS: Trust to Sharing Personal Data Information; WV: Willingnes to Value The Privacy of Personal Data
Source: Smart-PLS 4.1.1.4 Output, 2025

Table 4. Fornell-Larcker Criterion

	CO	EP	KP	LC	OE	PP	TS	WV
CO	0.864							
EP	0.514	0.865						
KP	0.519	0.561	0.847					
LC	0.297	0.144	0.214	0.856				
OE	0.463	0.463	0.520	0.473	0.857			
PP	0.484	0.576	0.456	0.501	0.634	0.846		
TS	0.614	0.612	0.487	0.326	0.558	0.541	0.865	
WV	0.626	0.607	0.580	0.363	0.526	0.482	0.757	0.865

Note. CO: Control Over Personal Data; EP: Experience in Personal Data Privacy; KP: Knowledge of Personal Data Privacy; LC: Local Culture; OE: Operational Efficiency; PP: Perceived Personalization; TS: Trust to Sharing Personal Data Information; WV: Willingnes to Value The Privacy of Personal Data
Source: Smart-PLS 4.1.1.4 Output, 2025

High-order construct measurement model

The evaluation of the high-order measurement model focused on reliability and validity, including construct reliability, convergent validity, and discriminant validity. The rho_a value for the personal data privacy (PDP) construct reached 0.879, exceeding the minimum acceptable level of 0.70 (Shela et al., 2023). Factor loadings of second-order indicators ranged from 0.763 (KP) to 0.873 (WV), confirming reliable representation of the high-order construct (Hair et al., 2017). Convergent validity was established through the average variance extracted (AVE), which recorded a value of 0.671—surpassing the 0.50 threshold (Sarstedt et al., 2022)—indicating that the construct captures a substantial proportion of indicator variance.

Table 5. Validity and Reliability

Construct	Dimensions	Loadings	Composite Reliability (rho_a)	Average Variance Extracted (AVE)
Personal Data Privacy	KP	0.763	0.879	0.671
	EP	0.808		
	CO	0.792		
	WV	0.873		
	TS	0.855		

Note. CO: Control Over Personal Data; EP: Experience in Personal Data Privacy; KP: Knowledge of Personal Data Privacy; TS: Trust to Sharing Personal Data Information; WV: Willingnes to Value The Privacy of Personal Data
Source: Smart-PLS 4.1.1.4 Output, 2025

Discriminant validity was verified through the Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker criterion. All HTMT values were below 0.85 (Benitez et al., 2020), with 0.697 for

PDP–perceived personalization (PP), 0.692 for PDP–operational efficiency (OE), and 0.700 for PP–OE, demonstrating clear construct distinctiveness. The Fornell-Larcker results further confirmed discriminant validity, as the square root of the AVE for each construct exceeded inter-construct correlations (Al-khadher et al., 2024). Collectively, the satisfactory reliability, convergent, and discriminant validity metrics affirm that the high-order measurement model is statistically sound and suitable for subsequent structural model analysis.

Table 6. Heterotrait-Monotrait (HTMT) Ratio

	LC	OE	PDP	PP
LC				
OE	0.546			
PDP	0.385	0.692		
PP	0.581	0.700	0.697	

Note. LC: Local Culture; OE: Operational Efficiency; PP: Perceived Personalization; PDP: Personal Data Privacy
Source: Smart-PLS 4.1.1.4 Output, 2025

Table 7. Fornell-Larcker Criterion

	LC	OE	PDP	PP
LC	0.856			
OE	0.473	0.857		
PDP	0.328	0.619	0.819	
PP	0.501	0.633	0.622	0.846

Note. LC: Local Culture; OE: Operational Efficiency; PP: Perceived Personalization; PDP: Personal Data Privacy
Source: Smart-PLS 4.1.1.4 Output, 2025

Structural model

In presenting the evaluation results for the structural model, this study refers to the procedure outlined by Sarstedt et al. (2022), which includes five main stages: testing for multicollinearity using the variance inflation factor (VIF), analyzing path coefficients, measuring R-square values, assessing predictive power using PLSpredict, and evaluating model fit using the standardized root mean square residual (SRMR) indicator.

Multicollinearity test

Multicollinearity testing is conducted to ensure there is no high correlation between independent variables that could interfere with model estimation. Referring to Sarstedt et al. (2022), a VIF value ≤ 5 indicates the absence of multicollinearity issues. Based on the test results, the VIF value for the personal data privacy construct against the two endogenous variables, operational efficiency and perceived personalization, was 1.212 for each, confirming that there was no high correlation between the exogenous constructs in the model. Thus, these results strengthen the validity of the model specifications and indicate that the estimation of relationships between constructs is not biased by multicollinearity.

Path coefficient analysis

The structural model was tested through path coefficient analysis to examine the relationships between variables in the research model. Based on the results in Table 8, all proposed hypotheses were found to be statistically significant. Personal data privacy has a positive and significant impact on perceived personalization ($O = 0.556$; $T = 5.876$; $P < 0.001$) and operational efficiency ($O = 0.578$; $T = 6.012$; $P < 0.001$), indicating that the perception of personal data protection plays an important role in enhancing service personalization and the operational efficiency of digital banks. Furthermore, the interaction between local culture and personal data privacy also shows a significant moderating effect on perceived personalization ($O = 0.108$; $T = 2.159$; $P = 0.031$) and operational efficiency ($O = 0.120$; $T = 2.650$; $P = 0.008$). This result confirms that the local cultural context strengthens the relationship between the perception of personal data protection and the two endogenous variables in this study.

Figures 3 and 4 demonstrate that local culture moderates the relationships between personal data privacy and its outcomes—perceived personalization and operational efficiency. The interaction plots show steeper slopes at higher levels of local culture, indicating that stronger cultural values enhance the positive effects of personal data privacy on both outcomes.

Table 8. Hypothesis Testing

	Hypothesis	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P-Value	Result
H1	Personal Data Privacy → Perceived Personalization	0.556	0.096	5.876	0.000	Accepted
H2	Personal Data Privacy → Operational Efficiency	0.578	0.096	6.012	0.000	Accepted
H3a	Local Culture* Personal Data Privacy → Perceived Personalization	0.108	0.050	2.159	0.031	Accepted
H3b	Local Culture* Personal Data Privacy → Operational Efficiency	0.120	0.045	2.650	0.008	Accepted

Source: Smart-PLS 4.1.1.4 Output, 2025

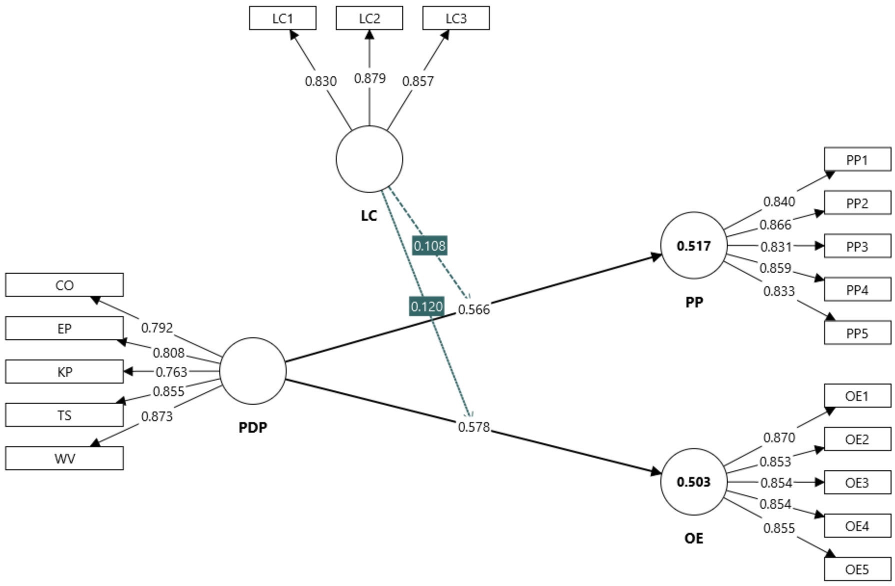

Figure 2. Bootsraping Model
Source: Smart-PLS 4.1.1.4 Output, 2025

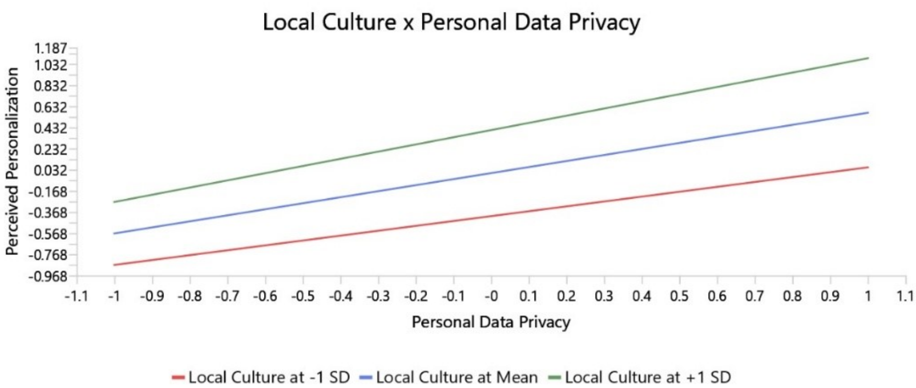

Figure 3. Interaction Effect of Local Culture x Personal Data Privacy on Perceived Personalization
Source: Smart-PLS 4.1.1.4 Output, 2025

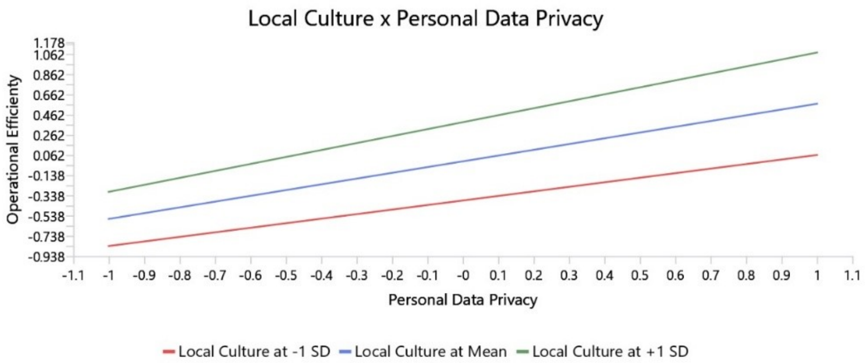

Figure 4. Interaction Effect of Local Culture x Personal Data Privacy on Operational Efficiency
Source: Smart-PLS 4.1.1.4 Output, 2025

R-square

The R-Square (R^2) value is used to measure how much of the variation in the endogenous variable can be explained by the exogenous variables in the structural model. In this context, the results of local culture moderation on the variables of perceived personalization and operational efficiency show R^2 values of 0.517 and 0.503, respectively, with adjusted R^2 values of 0.509 and 0.495. Referring to the guidelines of Hair et al. (2019), an R^2 value of 0.50 can be categorized as a moderate explanatory power of the model. This indicates that integrating personal data protection and local cultural context plays a crucial role in shaping users' perceptions of personalized and efficient digital services.

Predictive power (PLSpredict)

The results of the predictive evaluation show that all indicators of the endogenous variables, namely operational efficiency and perceived personalization, have positive Q^2predict values (0.299 – 0.368), indicating predictive relevance (Table 9). Additionally, the RMSE and MAE values in the PLS-SEM model are generally lower than in the linear model (LM), indicating better prediction accuracy (Table 9). This indicates that the structural model used is not only statistically fit but also capable of accurately predicting endogenous variables (Guenther et al., 2023).

Table 9. Predictive Power (PLSpredict)

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
OE1	0.340	0.724	0.576	0.756	0.591
OE2	0.331	0.749	0.593	0.787	0.614
OE3	0.349	0.749	0.579	0.780	0.601
OE4	0.340	0.783	0.623	0.804	0.635
OE5	0.315	0.742	0.572	0.784	0.592
PP1	0.299	0.721	0.534	0.734	0.556
PP2	0.347	0.754	0.605	0.749	0.592
PP3	0.328	0.768	0.594	0.781	0.611
PP4	0.368	0.762	0.581	0.762	0.585
PP5	0.313	0.790	0.627	0.783	0.629

Source: Smart-PLS 4.1.1.4 Output, 2025

Model fit

The suitability of the model in this study was evaluated using the standardized root mean square residual (SRMR) indicator to assess the fit between the structural model and empirical data. The selection of SRMR was based on the moderate complexity of the model and adequate sample size, in accordance with the recommendations of Sarstedt et al. (2022). The model fit in this study showed adequate results with an SRMR value of 0.057 for the saturated model and 0.069 for the estimated model, both of which are below the threshold of 0.08 as suggested by Guenther et al. (2023).

Table 10. Model Fit (SRMR)

	Saturated model	Estimated model
SRMR	0.057	0.069
d_ULS	0.547	0.814
d_G	0.287	0.338
Chi-square	344.641	421.111
NFI	0.858	0.826

Source: Smart-PLS 4.1.1.4 Output, 2025

Discussion

The results of this study indicate that personal data privacy has a positive and significant effect on perceived personalization (O = 0.556, T Statistics = 5.876, P-Value = 0.000), which suggests that the higher an individual's perception of their personal data protection, the greater their tendency to experience digital services that are relevant to their personal needs and preferences. Personal data privacy in this study is measured as a multidimensional construct consisting of five dimensions: knowledge of personal data privacy, experience in personal data privacy, control over personal data, willingness to value the privacy of personal data, and trust in sharing personal data information. Among these five dimensions, willingness to value the privacy of personal data is the most dominant dimension in shaping personal data privacy. This indicates that individual appreciation for the importance of personal data protection plays a crucial role in building trust in personalized digital services. Therefore, increasing consumer education and awareness regarding the value of personal data is a crucial strategy in building responsive and relevant digital services.

Furthermore, these findings align with previous research that also highlighted the importance of data privacy in shaping perceptions of service personalization. Van Buggenhout et al. (2023), and Zhang et al. (2025) demonstrate data protection or management. Meanwhile, Shin et al. (2025) also emphasize that when individuals feel safe and have autonomy over their personal data, they will be more open to communication and services designed based on personal preferences. Within the framework of digital marketing and customer relationship management, data privacy is not only a form of regulatory compliance but also a strategic instrument in strengthening loyalty and enhancing user experience. Therefore, a privacy policy that emphasizes respect for individual privacy rights will strengthen the perception of personalized services and drive the success of digital transformation in the banking sector.

Furthermore, this study also indicates that personal data privacy has a significant impact on operational efficiency (O = 0.578, T-statistic = 6.012, P-Value = 0.000). This suggests that a positive perception of personal data protection can enhance the operational efficiency of digital banks by promoting active customer participation in technology-based services. When customers feel safe and confident that their data is managed transparently, they are more willing to use digital services, which ultimately speeds up transaction processes and reduces reliance on manual processes. This finding aligns with the research by Martínez-Navalón et al. (2023), which emphasizes the importance of users' sense of security regarding privacy as a supporting factor for trust and engagement in digital banking applications. Additionally, Bueno et al. (2024) also revealed that the digitalization of services, when accompanied by strong data privacy protection, can significantly improve operational efficiency.

Interestingly, the influence of personal data privacy on perceived personalization is strengthened by the moderating role of local culture (O = 0.108, T Statistics = 2.159, P-Value = 0.031). The findings indicate that in societies characterized by strong social cohesion and interpersonal trust—such as those in eastern Indonesia—cultural values play a crucial role in shaping how individuals interpret and respond to data privacy practices. Specifically, cultural orientations rooted in collectivism and high-context communication, as described by Hofstede (2001), enhance individuals' sensitivity to trust and shared social norms. In collectivist societies, where group harmony and mutual trust are highly valued, data privacy is perceived not merely as an individual right but also as an expression of respect for social relationships. Consequently, when digital service providers demonstrate accountability and transparency in managing personal data, users perceive such actions as manifestations of cultural respect, thereby reinforcing their perception of personalized and trustworthy services.

This mechanism suggests that personalization in such cultural contexts is not solely a result of technological alignment but also a reflection of social resonance—users respond positively when their cultural expectations regarding trust, respect, and relational sensitivity are acknowledged. These findings align with Hofstede (2001) and Khan et al. (2024), who argue that collectivist cultures with high levels of uncertainty avoidance tend to emphasize interpersonal reliability and social assurance as prerequisites for adopting technology-based services. Thus, cultural attachment strengthens individuals' psychological readiness to share personal data when trust is established within culturally appropriate boundaries.

Moreover, local culture moderates the relationship between personal data privacy and operational efficiency (O = 0.120, T Statistics = 2.650, P-Value = 0.008). In cultural settings that emphasize social closeness and communal trust, individuals are more likely to actively use digital banking services when privacy assurance aligns with collective norms. From a socio-psychological perspective, this phenomenon reflects the concept of social capital, where the strength of community ties facilitates collective acceptance of technological innovation (Butt et al., 2024; Khazanchi et al., 2007). Personal trust and relationship-based interactions reinforce perceptions of system security and reliability, while relational personalization consistent with social values enhances loyalty and reduces resistance to innovation, ultimately improving banks' operational efficiency.

Overall, the moderating role of local culture underscores that digital transformation cannot be fully understood without considering cultural psychology. The findings suggest that in culturally rich and relationship-oriented societies such as Maluku, incorporating cultural sensitivity into privacy and personalization strategies is not merely optional but essential for building an inclusive, efficient, and trust-based digital ecosystem.

Conclusion and Implications

Theoretically, this study extends the growing body of literature on data privacy and customer data platforms (CDPs) by integrating local culture into the privacy–personalization–efficiency framework. The findings indicate that local cultural values not only influence users' acceptance of digital service personalization but also enhance operational efficiency when data privacy concerns are adequately addressed. These results suggest that models developed within Western or purely technological contexts may not fully capture behavioral dynamics in developing countries. By incorporating local culture as a moderating variable, this research provides a significant theoretical contribution to understanding the interaction among privacy perception, service personalization, and operational efficiency within diverse socio-cultural contexts such as Maluku, Indonesia.

Practically, the findings offer tangible implications for policymakers and banking institutions in designing adaptive digital strategies that align with local cultural values. Financial regulators and banks are encouraged to develop privacy policies emphasizing consumer transparency and control while embedding cultural sensitivity in the design and communication of digital services. Educational initiatives aimed at increasing consumer awareness of data value and protection should be prioritized to foster long-term trust and engagement. Nevertheless, this study acknowledges several limitations, particularly its geographical scope limited to four regions in Maluku and the use of cross-sectional data, which constrains the ability to draw causal inferences. Therefore, future research is recommended to expand the analysis to other provinces or adopt a longitudinal design to capture the evolving dynamics of culture and user behavior over time.

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