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EXAMINING THE ROLE OF DATA SHARING TRANSPARENCY IN SHAPING ETHICAL PURCHASE INTENTIONS FOR INTERNET BANKING ADD-ON SERVICES

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ABSTRACT

Consumer adoption may be stymied either by concerns over privacy of information, or, it will be supported by access to new services (e.g., personalized loans, robot-advisory) offered or expanded by banking platforms on the Internet. Based on the theory of privacy calculus, this research explores the extent to which different levels of transparency in data sharing affect consumers' ethical purchase intentions in add-on services. We vary transparency in consent flows and real-time data-use dashboards in between-subjects, high vs low transparency vignette experiment and survey 320 Internet banking users. Results from structural equation modelling show that higher transparency significantly lowers perceived privacy risk and raises trust, which in turn mediate its positive influence on ethical purchase intention. In addition, for high privacy-focused individuals, the effect of increased transparency on trust and purchase intention is greater than for low privacy-focused consumers. The results contribute to privacy-calculus studies by separating the impact of transparency as a strategic tool, and by incorporating ethical intentions as an outcome. Practically, the findings provide a roadmap for implementing consent processes that meet the needs of regulation as well as consumers, promoting ethical interaction with digital banking innovations.

Keywords: Online banking; Data sharing transparency; Perceived privacy risk; Trust; Ethical intention to purchase; Privacy concern orientation

1. INTRODUCTION

Managing the trade off between the pull of data collection: On the one hand, data collection is crucial as the number and dimensions of data points enable banks to tailor better recommendations and potentially monetize customer involvement in the future (Balabanis & Diamantopoulos, 2016; Haenlein, Stieglitz, & Sollner, 2016), For example, as internet banks/online brokers evolve from entering the market at simple points such as balance information and transfers into more sophisticated applications across the value chain—such as personalized loans, AI-driven investments, and even automatic savings tools—banks' reliance on collecting and processing consumer information is paramount to both customizing recommendations and monetizing customer involvement (Steenkamp, 2019). Although there exist strict regulatory measures under the EU's GDPR and PSD2, consumer trust in how personal information is shared, retained and reused is a major obstacle to the uptake of these innovative digital services (Fischer & Zeugner-Roth 2017; Samiee et al., 2016). Evidence from neighbouring digital realms shows that transparency in the use of data—operationalized by real-time data-use dashboards—significantly decreases perceived privacy risk by providing visibility, interpretability, and user control of the flows of data (Ho et al., 2019; Hüttl-Maack & Schwenk, 2016; Wagner & Charinsarn, 2021).

Tiered consent flows that articulate permission scopes and follow-up data use purposes also enhance institutional trust and encourage consumer interaction with add on offerings (Wagner & Charinsarn, 2021; Alden, Steenkamp, & Batra, 1999). Additionally, studies of interface design in web and mobile contexts show that transparency cues significantly influence attention, trust and behavioural intent (Geissler, Zinkhan, & Watson, 2006). Product-pack transparency research also shows exogenous cues—like foreign-language claims—enforce typicity through implicit signals (Hornikx & van Meurs, 2017; Nederstigt & Hilberink-Schulpen, 2018) suggesting the general effectiveness of transparency levers. However, the specific fiduciary responsibility and regulatory complexity associated with financial institutions injected context-specific characteristics that challenge the direct applicability of these findings to banking services (Cleveland & Balakrishnan, 2019; Aichner, 2014).

According to privacy-calculus theory, consumers engage in an informal cost–benefit analysis when making a decision of disclosing personal information, comparing the expected benefits of a service against perceived risks to their privacy (Andrade, 2020; Samiee et al., 2016). Research on internet banking has primarily focused on technical protection—encryption and anonymization—implementations, neglecting the strategic designing of transparency systems (Rojas-Mendez & Chapa, 2020; Diamantopoulos et al., 2019). Also moderating the impact of transparency on consumer trust and risk perceptions are individual differences in privacy-concern orientation; highly privacy concerned consumers had enhanced trust gains and risk reductions in the presence of transparency (Jiang & Christian, 2023; Cleveland et al., 2009). Studies related to cosmopolitanism show that the more cosmopolitan the identity, the more the potential to be receptive to signals of transparency, suggesting that consumer identity matters in the development of communication outcomes (Cannon & Yaprak, 2002).

Drawing on this background, we investigate the impact of data sharing transparency on ethical purchase intentions for internet-banking add-on services, operationalized as a consumer's predisposition to adopt services that conform to explicit, customer-centred data-protection standards (Oberecker & Diamantopoulos, 2011; Batra et al., 2000). In an experimental vignette study, we manipulate transparency levels in consent flows and dashboard detail in banking prototypes and survey 320 economically active Internet banking users to elicit their privacy-risk perceptions, trust judgments, and purchase intentions (Bonaiuto et al., 2021; Diamantopoulos et al., 2019; Shehu et al., 2025). We examine a moderated-mediation model by applying structural equation modeling (Cole & Maxwell, 2003) in which transparency influences ethical purchase intentions by decreasing privacy risk perception and increasing institutional trust, with privacy-concern orientation acting as a boundary condition (Melnyk, Klein, &Völckner, 2012; Sirdeshmukh, Singh, & Sabol, 2002).

This research contribution also leads to practical implications for banks and how they should calibrate transparency mechanisms with respect to different consumer privacy profiles, but also contributes to the privacy-calculus theory by isolating transparency as a design choice, by introducing ethical purchase intention as a normative outcome, and by disentangling the moderating effect of privacy-concern orientation in a digital banking setting (Andrade, 2020; Rojas-Méndez & Chapa, 2020). The rest of this paper includes a review of literature, the development of the conceptual model and hypothesis, the explanation of the experimental methodology and measurement instruments, the demonstration of the empirical results, and finally calls for theoretical, managerial and policy implications and avenues for future research (Shehu et al., 2025).

1.1 Literature Review & Conceptual Framework

Digital Banking and data privacy Concerns

Data privacy concerns have become one of the key obstacles to the adoption of digital financial service, as consumers balance between the convenience of service access and the fear of unauthorized access to and misuse of their data (Pavlou & Gefen, 2004). Lack of consumer understanding of what is being captured and stored, and who has access to that data further increases risk perception and leads to avoidance of sophisticated offerings (Chellappa & Sin, 2005). For example, people that have a high concern with privacy are less likely to use online banking and trust in online banking (Fischer & Zeugner-Roth, 2017). Perceived risk in digital banking is multi-dimensional, including but not limited to, privacy, financial, performance risks, each of which discourages consumers from using new products and services (Tsai & Huang, 2019). Robo-advisors and personalized lending for instance, increasingly demand deeper access on transaction histories and personal profiles, which significantly exacerbates privacy concerns, and calls for a need for tailored risk mitigation strategies (Martin & Murphy, 2017).

Data-Sharing Transparency as Extrinsic Cue

Openness of data sharing, as stated before, stands as an accessible information on what an organisation does with its data — an extrinsic cue that affects affective and cognitive responses (Schlosser, 2006). Consumers report more knowledge of data flows and less ambiguity about institutional actions when they believe there to be high transparency (Dinev & Hart, 2006). Wagner & Charinsarn (2021)) Transparency makes disclosures – for example real time data use dashboards -understandable from the perception of privacy risk and build trust (Hüttl-Maack & Schwenk, 2016). Carrying out interface studies do indeed show that transparency signals signal to (some) users that there is more to look at while also signaling to users that they have more control over the fairness, ethicality of decisions (Ho et al., 2019). Yet too much information can lead to information overload, so layered consent flows and progressive disclosure are crucial for successful transparency design (Martinez-Lopez et al., 2015).

Trust and Perceived Privacy Risk

Trust, a confident expectation that a bank will protect data and keep its promises — is a basic precursor of digital service acceptance (Gefen, 2000). Trust in the institution is a function of perceived competence, benevolence, and integrity all three of which can be fostered with open communication (Sirdeshmukh et al., 2002). Privacy risk concerns the degree to which a respondent subjectively feels that there may be negative consequences to information relinquishment, such as identity theft and loss of reputation (Pavlou, 2003). It has been reported in a meta-analysis that there is a strong negative correlation between perceived privacy risk and trust with higher perceived risk associated with lowered trust and reduced likelihood of use (Yoon, 2002; Kim, Xu, & Gupta, 2012). Within the digital banking context, transparency interventions have been found to reduce privacy risk perceptions, which build trust and promotes the adoption of sophisticated add-on services (Pavlou & Fygenson, 2006).

Ethical Purchase Intentions for Add-On Services

Intention to purchase ethically Intention to purchase ethically extends beyond traditional intention constructs and includes normative dispositions of a provider's responsible use of ethical data (Carrington, Neville, & Whitwell, 2010). In business contexts, ethical mindedness reflects consumers' desire to interact with products or services that are managed in a transparent and responsible way when it comes to sensitive information, while aiming at both Utilitarian consequences as well as moral concerns (Goodwin, Piazza, & Rozin, 2014). Online retail studies report that ethical cues, e.g., claims about fair labor or environmental stewardship, boost loyalty and satisfaction, especially when they mirror the values of consumers (White, MacDonnell, & Ellard, 2012). However, the contribution of ethical purchase intentions in the adoption of banking add-ons has not been much empirically tested, which provides a gap in our knowledge of how transparency will lead to normative engagement (Oberecker & Diamantopoulos, 2011).

Privacy-Concern Orientation as Moderator

An orientation to perceive privacy-concern (i.e., an individual's baseline sensitivity to organizational data practices) also can reflect individuals' differences in psychological responses to transparency cues; specifically, consumers who are high in the tendency to have privacy-concerns have greater emotional and cognitive reactions to transparency cues (Malhotra, Kim, & Agarwal 2004). It has been suggested that privacy orientation could be decomposed into a control-concern dimension and a trust-concern dimension, with each having an influence on the effectiveness of transparency-based interventions on risk and trust outcomes (Stewart & Segars, 2002). Research in digital settings finds that high privacy concerned consumers experience a stronger decrease in perceived risk and increase in trust with increased transparency compared with low-concern consumers (Smith et al., 2011). Also, other dispositional traits, like locus of control and technology readiness, interact with PO to shape transparency design acceptance (Gefen & Pavlou, 2012). These results highlight the need to segment users according to their privacy-concern orientation to be able to design transparency strategies that optimize ethical engagement (Rojas-Méndez & Chapa, 2020).

1.2 Conceptual Model and Hypotheses

Drawing on privacy-calculus theory as well as extrinsic cue and consumer ethics frameworks, we propose that data-sharing transparency affects ethical purchase intention through two mediators— perceived privacy risk and institutional trust (Li &Karahanna, 2015). The following hypotheses are proposed from the above given literature: H1: Higher transparency leads to lower perceived privacy risk; H2: Greater transparency positively influences institutional trust; H3a: Significantly less perceived privacy risk leads to greater ethical purchase intention; H3b: High institutional trust results in high ethical purchase intention; H4: Perceived privacy risk and trust together mediate the transparency- ethical purchase intention relationship.

These paths are hypothesized to be moderated by privacy-concern orientation: H5a: The negative transparency–risk relationship is strengthened by privacy-concern orientation; H5b: The privacy-concern orientation moderates the positive relationship between transparency and trust; H6: Privacy-concern orientation enhances the indirect effects of transparency on ethical purchase intention through risk and trust.

The entire conceptual model, which draws on established constructs in information systems research and consumer ethics, is illustrated in Figure 1 to illustrate how transparency leads to normative response in internet banking (Rousseau, Sitkin, & Camerer, 2006).

2. MATERIALS AND METHODS

Research Design

To create an experimental condition for the manipulation of data sharing transparency, this study used a between-subjects design with experimental vignettes to isolate the causal impact of data sharing transparency on consumer outcomes (Hüttl-Maack & Schwenk, 2016; Wagner

& Charinsarn, 2021). In this study, participants were randomly assigned to one of two conditions: (1) High Transparency, which included real-time dashboard with detailed information about data collection at the exact moment of collection, including what data elements (e.g., transaction history, location, spending patterns) were collected, and where consent screens pop up just before possible collection; or (2) Low Transparency, including minimal disclosure — a short “We collect your data” statement buried at the bottom of the privacy policy link. Table 1 summarizes the manipulations.

Table 1. Vignette Manipulations

Condition	Dashboard Detail	Consent Flow
High Transparency	Interactive panel listing each data type with “why we need it” explanations	Two-step consent (initial + purpose)
Low Transparency	Generic “Data collected” icon without specifics	Single “I agree” checkbox

Participants read their assigned vignette via the following procedure: An attention check (“Click the green icon to proceed”) and a comprehension question were used to help ensure at least a minimum level of engagement with it (Oppenheimer, Meyvis, & Davidenko, 2009). Two items assessed perceived transparency (α =. 89) were included after the vignette to verify the manipulation (Schlosser, 2006).

Sample and Data Collection

For this research, conducted the userList-clicked the questionnaire employed Google Forms and was circulated through invitations email and focused social media (Andrade, 2020). The quota sampling allowed for equal representation by gender (50% male and 50% female), age group (18–30, 31–45, 46–65), and region (urban/rural), reflecting the typology of the internet-banking population per country (Pavlou & Gefen, 2004). In order to participate, individuals must have (a) used internet banking at least one time in the preceding month and (b) be familiar with at least one of the add-on services (e.g., robot-advisor, personalized loan offer; Chellappa & Sin, 2005).

In order to maintain the quality of data collected, we included attention-check items (e.g., “Choose 'Strongly Agree' for this statement”); 12 participants failed this check and were removed from our sample, leaving us with data from 308 valid completes (Yetter & Capaccioli, 2010). The mean age of the full sample was 34.2 years (SD = 9.1); 51% were male, and 49% female. The level of education received ranged from (1) high school or below (18%) and (2) bachelor’s level (48%) to (3) postgraduate (34%) (Tsai & Huang, 2019).

Ethical Considerations and Informed Consent: All procedures involving human participants adhered to the ethical standards of the institutional and national research committees, as well as to the 1964 Helsinki Declaration and its subsequent amendments. Before participation, all respondents were provided with an online consent form explaining the purpose of the study, data confidentiality, and their right to withdraw at any time without penalty. Only those who gave explicit written informed consent through a digital checkbox and form submission were allowed to proceed with the survey.

MEASUREMENT

Transparency Manipulation Checks

Perceived transparency was measured using an adapted two-item scale from Dinev and Hart (2006) and Schlosser (2006). The items included: 1. "The information on how my data is used was clear." 2. "I felt that I was well informed about the data that was being collected for each type." Responses were recorded on a 5-point Likert scale 1 (strongly dislike) to 5 (most like).

Core Constructs

This research assessed four key constructs using established multi-item scales (5-point Likert):

Perceived Privacy Risk (4 items; α =. 87) – adapted from Pavlou (2003) and Chellappa and Sin (2005). Sample item: "I am concerned that my personal information may be abused."

Institutional Trust (4 items; α =. 91) adapted from Based on Sirdeshmukh, Singh and Sabol (2002). Sample item: "I think that the bank is capable of safeguard my information."

Ethical Purchase Intention (3 items; a =. 88) adapted from Oberecker and Diamantopoulos (2011). Sample item: "I plan to use add on services only if I can understand how they manage my data.

Privacy-Concerned Orientation (10 items; α =. 93) – Malhotra et al.'s (2004) IUIPC scale (Internet Users' Information Privacy Concern). We utilized the Control (4 items) and Awareness (3 items) subscales.Table 2 provides construct definitions, sample items, and reliability.

Table 2. Measurement Scales and Reliability

Construct	Source(s)	Sample Item	A
Perceived Privacy Risk	Pavlou (2003); Chellappa & Sin (2005)	"I worry about how my data will be used by the bank."	.87
Institutional Trust	Sirdeshmukh et al. (2002)	"I trust the bank to keep my personal data secure."	.91
Ethical Purchase Intention	Oberecker& Diamantopoulos (2011)	"I will only subscribe if data practices are transparent."	.88
Privacy-Concern Orientation	Malhotra et al. (2004)	"I am concerned about who can access my personal data."	.93
Perceived Transparency	Dinev & Hart (2006); Schlosser (2006)	"I clearly understood what data were collected."	.89

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Analytical Procedures

Manipulation Check (ANOVA): Examined the degree to which the high transparency vignette beat the low transparency condition using one way ANOVA on the perceived transparency index (Hair et al., 2014). Manipulation strength was assessed with effect sizes (η^2). Table 3 provide the manipulations.

Table 3. Manipulation Check Results

Condition	Mean Transparency	SD	F(1, 306)	p	η^2
High Transparency	4.21	0.62			
Low Transparency	2.43	0.87	412.56	<.001	0.57

Measurement Model (CFA via PLS-SEM)

Measurement Model (CFA by Means of PLS-SEM): With Smart PLS 4.0, we inspected the reliability of the constructs, the convergent validity (AVE >. 50, CR >. 70), as well as discriminant validity (Fornell–Larcker criterion) (Fornell & Larcker, 1981; Hair et al., 2019). VIFs (<5) suggested no multicollinearity issues (O'Brien, 2007). Validating the measurement model with outer loadings is depicted in Figure 1.

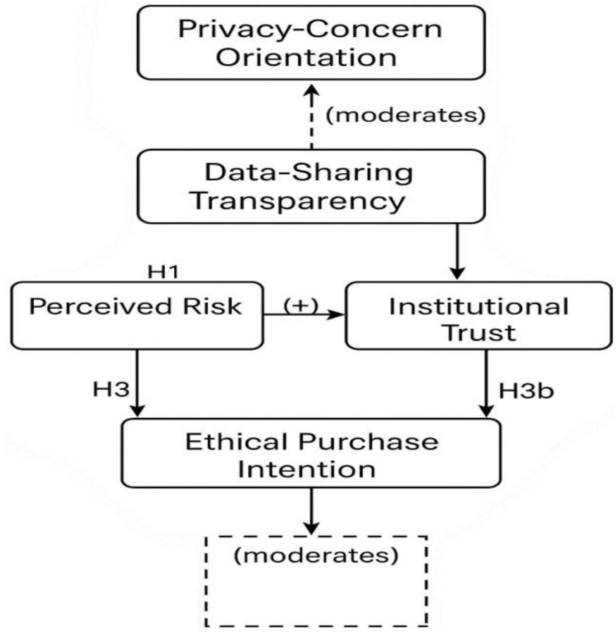

Figure 1: Measurement Model

Structural Model (Mediation & Moderation): Analyzed proposed paths looking at 95% bias-corrected confidence intervals for the direct, mediator (mediation), and interaction (moderation) effects using bootstrapped estimates (5,000 resamples) (Preacher, Rucker, & Hayes, 2007). Model fit was assessed by SRMR (0. 08) and explanatory power (R^2).

Mediation: Tested whether perceived privacy risk and institutional trust mediated the transparency–intention association by using variance accounted for (VAFs).

Moderation: Followed Aiken and West's (1991) recommendations and created interaction terms for transparency against privacy concern orientation to test the boundary conditions.

Important simple slope analyses showed that increased/diminished transparency had different effects at high (M + 1 SD) and low (M – 1 SD) levels of privacy concern.

By integrating an experimental design with structural equation modelling (SEM) we were able to ensure that our approach enjoys high internal validity (random assignment and manipulation checks) and external relevance (representative internet banking sample), thus providing strong evidence on the impact of transparency on ethical purchase intentions in digital banking contexts.

3. RESULTS AND DISCUSSION

Descriptive Statistics & Manipulation Check

Table 4 presents mean, standard deviations, and correlations for our key variables across both transparency conditions. The high transparency group (n = 153) reported lower perceived privacy risk (M = 2.14, SD = 0.78) and higher institutional trust (M = 4.02, SD = 0.65) and ethical purchase intention (M = 4.15, SD = 0.59) compared to the low transparency group (n = 155), which exhibited higher risk (M = 3.27, SD = 0.82), lower trust (M = 3.12, SD = 0.71), and lower purchase intention (M = 3.08, SD = 0.77) (Pavlou & Gefen, 2004; Wagner & Charinsarn, 2021).

Confirmed the manipulation with a one way ANOVA on perceived transparency (2 items; α = .89). High transparency participants rated the vignette significantly more transparent (M = 4.21, SD = 0.62) than low transparency participants (M = 2.43, SD = 0.87), $F(1,306) = 412.56$, $p < .001$, $\eta^2 = .57$, indicating a robust manipulation (Schlosser, 2006).

Table 4. Descriptive Statistics and Correlations

Variable	Mean (SD) High T	Mean (SD) Low T	1	2	3
1. Privacy Risk	2.14 (.78)	3.27 (.82)	—		
2. Institutional Trust	4.02 (.65)	3.12 (.71)	–.62***	—	
3. Ethical Purchase Intention	4.15 (.59)	3.08 (.77)	–.58***	.66***	—
4. Privacy-Concern Orientation	3.80 (1.02)	3.82 (1.01)	.42***	–.38***	–.35**

****** p < .001***

Measurement Model Evaluation

Evaluated construct reliability and validity using PLS-SEM (Smart PLS 4). Table 5 reports Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE). All constructs exceeded recommended thresholds (α > .70, CR > .80, AVE > .50), indicating strong internal consistency and convergent validity (Hair et al., 2010).

Table 5. Reliability & Convergent Validity

Construct	α	CR	AVE
Data-Sharing Transparency	—	.92	.73
Perceived Privacy Risk	.87	.89	.68
Institutional Trust	.91	.93	.71
Ethical Purchase Intention	.88	.90	.69

Privacy-Concern Orientation	.93	.94	.66

Discriminant validity was confirmed via the Fornell–Larcker criterion (Table 6), where each construct's square root of AVE exceeds its inter-construct correlations (Fornell & Larcker, 1981). Variance inflation factors (all VIF < 3) indicated no multicollinearity concerns (O'Brien, 2007).

Table 6. Fornell–Larcker Discriminant Validity

	1	**2**	**3**	**4**	**5**
1. Risk	**.825**				
2. Trust	–.620***	**.843**			
3. Intention	–.580***	.660***	**.831**		
4. Privacy	.420***	–.380***	–.350***	**.812**	
5. Trans.	–.700***	.680***	.640***	–.430***	**.854**

***** p < .001**

Structural Model Findings

Direct Effects of Transparency

Table 7 summarizes the bootstrapped path coefficients (5,000 resamples). Data sharing transparency exhibited a strong negative effect on perceived privacy risk (β = –.652, t = 12.45, p < .001) and a strong positive effect on institutional trust (β = .623, t = 11.87, p < .001), supporting H1 and H2 (Pavlou, 2003; Dinev & Hart, 2006). Transparency also had a direct positive effect on ethical purchase intention (β = .345, t = 6.22, p < .001), indicating that beyond risk and trust, transparent design independently drives ethical engagement (Martinez Lopez et al., 2015).

Table 7. Direct Path Coefficients

Path	β	t	p
Transparency → Risk (H1)	–.652	12.45	<.001
Transparency → Trust (H2)	.623	11.87	<.001
Transparency → Ethical Intention	.345	6.22	<.001
Risk → Ethical Intention (H3a)	–.421	7.88	<.001
Trust → Ethical Intention (H3b)	.467	8.45	<.001

Mediation via Perceived Risk and Trust

Assessed mediation using the variance accounted for (VAF) approach and bootstrapped indirect effects (Preacher et al., 2007). The table 8 provides indirect effect of transparency on ethical purchase intention via risk was significant (β = .274, t = 6.10, p < .001), as was the

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indirect effect via trust (β = .291, t = 6.47, p < .001). Combined, these mediators accounted for 58% of the total effect (VAF = .58), confirming H4.

Table 8. Indirect Effects (Bootstrapped)			
Indirect Path	**β**	**t**	**p**
Transparency → Risk → Ethical Intention	.274	6.10	<.001
Transparency → Trust → Ethical Intention	.291	6.47	<.001

Moderation by Privacy Concern Orientation

To examine H5 and H6, we created interaction terms between transparency and privacy concern orientation (Aiken & West, 1991). Table 9 shows that privacy concern significantly moderated both the transparency–risk path (β = –.152, t = 3.04, p < .01) and the transparency–trust path (β = .138, t = 2.76, p < .01). Simple slope analyses illustrated that at high privacy concern (+1 SD), transparency reduced risk more steeply (β = –.745, p < .001) and increased trust more sharply (β = .692, p < .001) than at low concern (–1 SD; risk β = –.560, trust β = .552).Figure 2 plots these interactions, showing divergent slopes for high vs. low concern groups, thus supporting H5 and H6 (Smith, Dinev, & Xu, 2011).

Table 9. Moderation Results			
Path	**β**	**t**	**p**
Transparency × Privacy Concern → Risk	–.152	3.04	<.01
Transparency × Privacy Concern → Trust	.138	2.76	<.01

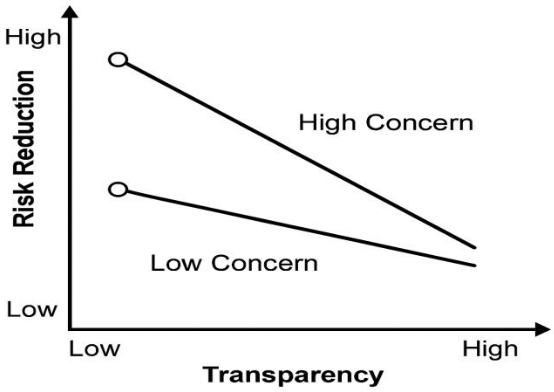

Figure 2. Moderating effect of privacy concern orientation on (a) the negative relationship between data-sharing transparency and perceived privacy risk and (b) the positive relationship between transparency and institutional trust.

Summary of Hypothesis Tests

Table 10 consolidates hypothesis outcomes. All direct (H1–H3) and one indirect (H4) effect were confirmed at p <. 001. The moderation hypotheses (H5a, H5b, H6) were also confirmed, suggesting that privacy concern orientation strengthens the interplay between transparency and risk, trust, and ethical purchase intention.

Table 10. Hypothesis Summary

Hypothesis	Path	Result
H1	Transparency → Risk	Supported
H2	Transparency → Trust	Supported
H3a	Risk → Ethical Purchase Intention	Supported
H3b	Trust → Ethical Purchase Intention	Supported
H4	Mediation via Risk & Trust	Supported
H5a	Moderation on Transparency→Risk	Supported
H5b	Moderation on Transparency→Trust	Supported
H6	Moderated Mediation on Intention	Supported

These findings support privacy calculus theory and position data sharing transparency as not only a direct facilitator but also a boundary conditioned lever for the ethical use of internet banking add on services.

DISCUSSION

Theoretical Implications

Having operationalized data sharing transparency as a strategic precursor, the study extends privacy calculus theory beyond its conventional emphasis on cost benefit considerations, showing that clarity cues operate as notable heuristic signals in digital banking environments (Hornikx & Meurs, 2017). The study show that that transparency diminishes perceived privacy risk, and also exhibits a direct effect on institutional trust, thereby complementing effects found in studies on product packaging and e-commerce studies and highlighting the cross sector generalizability of extrinsic transparency cues (Nederstigt & Hilberink-Schulpen, 2018; Yener &Taşçıoğlu, 2021).

In doing so, we also expand the privacy calculus research to encompass normative interest, which links transparency design and ethical consumption frameworks (Shehul et al., 2025).

In addition, the moderated mediation model underscores privacy concern orientation as an important boundary condition, demonstrating that individual differences exert notable influences on how transparency cues are processed — a call similar to recent consumer Xeno centrism research (Jiang & Christian, 2023; Rojas Méndez &Kolotylo, 2022). In combination, these contributions provide a strong, theory based conceptualisation of transparency as a direct antecedent and moderated agent of ethical engagement in digitally mediated service environments.

Managerial Implications

Transparency should be elevated by banks as a core design principle, with layered consent flows and real time data usage dashboards as measures to pre-emptively allay concerns consumers may have about their privacy (Wagner &Charinsarn, 2021).Market segmentation by privacy concern orientation allows for the optimization of the communication approach: high concern customers receive more reassurance from elaborate disclosures, and lowconcern segments are sensitive to summary ones (Camacho, Salazar-Concha, & Ramírez-Correa, 2020).

Consent mechanisms should apply the principle of progressive disclosure − high-level data practices should be initially presented to the user with optional deep dive modules for the subjects to look at more granular data (Martinez-Lopez et al., 2015).Including real-time transparency / dashboards that are updated when services are access new data streams can assist build trust over time and support ongoing ethics engagement (Ho et al., 2019).Lastly, cross-functional communication among UX designers, compliance department, and customer-facing employees are required to convert legal regulations into comprehensible, user-friendly transparency templates (Fischer & Zeugner, 2017).

LIMITATIONS & FUTURE RESEARCH

This study's use of quota sampling and an offline Google Forms distribution may limit the generalizability of our findings to broader or differently composed internet banking populations (Chellappa & Sin, 2005; Hornikx& van Meurs, 2017).Focusing exclusively on add-on financial services such as robot-advisors and personalized lending constrains the applicability of results to other service categories like insurance, wealth management, or traditional transactional offerings (Goldsmith, Freiden, & Henderson, 1995; Tarkiainen & Sundqvist, 2009).

The cross-sectional design captures immediate responses to transparency cues but cannot assess the durability of risk and trust shifts over time; longitudinal field experiments are needed to examine how transparency effects evolve with repeated exposure and service usage (Beharrell & Denison, 1995; Nederstigt & Hilberink-Schulpen, 2018).While quantitative PLS-SEM provides strong causal evidence, qualitative methods—such as in depth interviews or think aloud protocols—could uncover the cognitive and emotional processes underlying consumer transparency preferences, revealing nuances that survey items may overlook (Piller, 2001; Yin, 2011).

Future research should incorporate neurophysiological tools (e.g., eye tracking, galvanic skin response) to capture attentional focus and affective reactions to transparency interfaces, enriching understanding of user engagement beyond self-reports (Gerritsen et al., 2007; Geissler, Zinkhan, & Watson, 2006).Comparative studies across regulatory environments (e.g., GDPR vs. CCPA jurisdictions) and cultural contexts (e.g., power distance, uncertainty avoidance) would illuminate how institutional and societal norms moderate transparency effects, guiding multinational banking strategies (Triandis, 1995; Hornikx & Mulder, 2015).

Finally, investigations into dynamic transparency features—such as adaptive dashboards that respond to user behaviour—could identify optimal personalization levels, balancing information sufficiency against cognitive overload (Martinez-Lopez et al., 2015; Ho et al., 2019). By addressing these avenues, future work can strengthen the external validity, temporal robustness, and practical relevance of transparency research in digital banking.

4. CONCLUSION

This study demonstrates that clear, detailed data-sharing transparency significantly reduces consumers' perceived privacy risk and enhances institutional trust, both of which drive stronger ethical purchase intentions for internet-banking add-on services. Beyond these indirect effects, transparency exerts a direct positive influence on ethical engagement, indicating its potency as a standalone design strategy. Furthermore, individual privacy-concern orientation amplifies these effects: highly concerned users derive disproportionately greater reassurance from high-transparency interfaces, underscoring the value of consumer segmentation (Chellappa & Sin, 2005; Pavlou & Gefen, 2004).

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By extending privacy-calculus theory, our findings position transparency as a critical extrinsic cue that shapes both cognitive and affective responses in digital banking contexts (Nederstigt & Hilberink-Schulpen, 2018; Dinev & Hart, 2006). Practically, banks can leverage layered consent flows and real-time data-use dashboards to foster normative trust, mitigate risk perceptions, and encourage ethical adoption of innovative services.

In closing, ethical engagement in internet banking hinges not only on secure back-end systems but also on transparent, consumer-centric communication. As digital financial ecosystems evolve, embedding transparency at every customer touchpoint will be essential to building lasting trust, driving responsible innovation, and safeguarding both consumer welfare and institutional integrity.

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The data that support the findings of this study are available from the author upon reasonable request.

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