BEYOND SEAMLESSNESS: AN EFFORT–REWARD IMBALANCE AND PSYCHOLOGICAL REACTANCE PERSPECTIVE ON THE VALUE OF FRICTION IN AI-ENABLED PHYGITAL RETAIL

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Abstract

The customer journey is now frictionless for 10 years, but the AI systems now deeply entrenched in the "phygital" (physical + digital) stores regularly add friction: biometric checks, one-time-password verification and identity-confirmation steps are slowing customers down to keep them safe and personalised. This study confronts the question of whether such friction, created by AI, is always bad or can be accepted or even appreciated in certain well-defined circumstances. Based on the Effort–Reward Imbalance (ERI) theory (Siegrist, 1996) and Psychological Reactance Theory (Brehm, 1966) a conceptual model was developed and tested through questionnaires for 311 urban consumers who had visited AI stores for shopping in the last three months. Based on reliability analysis, correlation analysis and path analysis through hierarchical regression, it was found that the perceived effort increases the imbalance of effort–reward, and the perceived reward decreases the imbalance of effort–reward, which in turn affects reduction in the level of satisfaction with the journey. If the friction is perceived as being security justified, the increase in psychological reactance is much reduced. This reactance then decreases satisfaction and intention to continue. The results validate a "value of friction" hypothesis: friction justifies the value provided, and is accepted without resistance, while friction out of proportion or lack of explanation causes loss of satisfaction and loyalty.

Keywords: phygital retail; AI-enabled customer journey; friction; effort–reward imbalance; psychological reactance; consumer autonomy; security; continuance intention

JEL Classification: M31.

1. Introduction

For the last 10 years, the focus in retail tech has been on frictionless commerce. All the innovations around self-checkout, one-click payments, cashier-less stores, and AI-driven recommendation engines were based on one basic principle: Every extra step from the moment a consumer decides to make a purchase to the moment it is completed is a cost that needs to be reduced (Klaus, 2021). It has become even more pronounced in the quest for seamlessness, with "phygital" retail, the deliberate integration of physical stores

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with digital, AI-powered touchpoints like smart mirrors, computer-vision-based checkout, conversational assistants, and biometric verification.It has become even more apparent in the pursuit of seamlessness, with "phygital" retail, where digital, AI-enabled touchpoints like smart mirrors, computer-vision-based checkout, conversational assistants and biometric verification are deliberately integrated into physical stores (Batat, 2022; Jacob et al., 2021; Lemon & Verhoef, 2016).

But those very AI systems that will make our lives easier have sneaked in some new frictions. At checkout, the customer is asked to stop, comply and wait when he or she is asked to verify the face or fingerprints; the one-time-password (OTP) for high-value purchases; the step-up authentication when the AI system detects unusual behaviour; and consent prompts for data-driven personalisation all call for customer stop, comply and wait. The push toward frictionless self-service is now often described as a point of tradeoff: Security and fraud-prevention considerations always involve steps taken back in the journey, and adding these steps must be balanced with the push toward frictionless self-service. People now start talking about the need to turn friction into a design parameter, and make sure it is not over- or under-engineered, but optimally engineered, in the right place, for the right purpose.

This paper does not assume this, but takes it as a proposition worthy of testing. It builds on two widely used theories from fields outside of mainstream retail studies: Effort–Reward Imbalance (ERI) theory, from the field of occupational health psychology (Siegrist, 1996) and Psychological Reactance Theory, from social psychology (Brehm, 1966) to explore where and when friction with AI is beneficial, and where and when it is harmful, for the customer journey. ERI theory provides a perspective on the "value" side of friction: friction is not bad, it's only bad when there's insufficient value to match the effort (security, personalisation, trust); friction is strain in and of itself. A lens on the side of "autonomy" would be provided by reactance theory, which posits that friction becomes an expense when it is perceived as an outside system that is limiting the shopper's freedom to shop the way they want, thereby creating a motivational need to avoid it.

How does the use of AI with effort affect perceived imbalance, and what is the effect of the reward? (2) Does the use of AI with effort increase the perceived imbalance and does the reward buffer the effect? (3) Is psychological reactance linked to negative outcomes?(4) Is perceived autonomy restriction related to negative outcomes? (3) Does an increased association between autonomy restriction and reactance occur when friction is viewed as an element of security justification? (4) Does the decrease in journey satisfaction and in intention to continue due to imbalance and reactance occur simultaneously?

The paper makes three contributions. It brings ERI theory (which has been applied almost exclusively in occupational-stress research) into the domain of

AI retail applications, and extends the notion of customer effort to a reciprocity problem rather than merely a cost problem. Secondly, it defines "security justification" as a boundary condition which reduces the reactance, providing a more specific answer to the "personalisation paradox" that has been reported in the latest research on AI in marketing. Third, it provides the retailer with an evidence-based argument in designing "value-adding friction" instead of "default frictionlessness". The rest of the paper summarizes the two theories and phygital-retail literature, constructs seven hypotheses and a conceptual model, outlines the survey procedure, presents the results and offers some theoretical and managerial implications.

The theoretical background is provided, and a hypothesis is formulated.Theoretical background and formulation of the hypothesis.

2. Theoretical Background and Hypothesis Development

2.1 Phygital Retail and the Friction Paradox

Phygital retail is a conscious blend of physical and digital experiences that allows the customer's journey to seamlessly shift between the two points (Batat, 2022; Johnson & Barlow, 2021). Phygitality is not just an overlay of existing channels (Klaus, 2021) and the elimination of friction is a key design goal for phygitalisation. (Lemon & Verhoef, 2016; Jacob et al., 2021). At the heart of this is AI: computer vision, biometrics, and recommendation engines make 'walk in, walk out' and 'scan and go' formats possible.

But it is also the AI foundation that makes things convenient that makes things convenient and often needs verification. The more frictionless formats become, the more that retailers are going to be susceptible to new vulnerabilities (theft, fraud, identity misuse), and need to re-introduce checks at certain touchpoints along the way. This isn't a frictionless path, but one that is frictionless in some places and slowed in others as AI smooths out some aspects of it and slows others down on purpose. The field of phygital-retail exists, but existing research has looked at friction as a thing to be minimised by definition – not whether some friction is functional, rather than dysfunctional, when designed properly.

2.2 Effort–Reward Imbalance Theory

Effort–Reward Imbalance theory was developed to explain stress related strain in an occupational setting: The theory suggests that psychological and physiological strain is caused not by effort alone, but by an imbalance between effort and reward (Siegrist, 1996). The central reciprocity logic of the model is supported by a large number of studies in occupational contexts (van Vegchel et al., 2005) and the principle of 'costs' versus 'gains' applies to other social transactions where costs are involved besides paid work (Karasek & Theorell, 1990).

The interaction between the shopper and an AI-based retail system can be structured as a similar process as that of ERI: The shopper invests effort (time, cognitive effort, physical effort, etc.), exchanges this effort for a reward that the system calculates (security assurance, personalised offers, quicker visits in the future, etc.), and the system itself does not control the rules that govern the interaction. When applied to this context, ERI theory suggests that the effort verification steps enabled by AI are not inherently dissatisfying, when authentication is not.When applied to this context, ERI theory predicts that the effort verification steps enabled by AI are not inherently dissatisfying, when authentication is. It is important whether the reward is viewed as being in line with that effort. As the effort level increases and the perceived reward level decreases, a strain–satisfaction imbalance arises, which, similar to the occupational ERI literature, should lead to reduced satisfaction with the journey itself, here termed consumer strain.

H1: Perceived effort is positively associated with effort–reward imbalance.

H2: Perceived reward is negatively associated with effort–reward imbalance.

H3: Effort–reward imbalance is negatively associated with customer journey satisfaction.

2.3 Psychological Reactance Theory

Psychological Reactance Theory suggests that if a person's freedom is threatened or denied, then there is a motivational arousal which will manifest itself in various forms of resistance, irritation, or non-compliance (Brehm, 1966; Brehm & Brehm, 1981). Reactance is well documented in the marketing literature as a response to unsolicited recommendations and prescriptive advice (Fitzsimons & Lehmann, 2004), and has become a key explanatory mechanism in recent AI-marketing research: consumer experiences of algorithmic systems that override their preferences, default choices without consent, or that are known to restrict the range of visible options have been shown to lead to reductions in satisfaction and adoption (Longoni et al., 2019; Nokhiz & Ruwanpathirana, 2025; Oh et al., 2025).

AI enabled phygital friction is a potential source of reactance as several of its steps are irrefutable: a shopper may not opt-out of biometric verification and still be able to checkout for a purchase without payment; a shopper may not be able to skip the OTP step to complete a high value transaction. If the shoppers feel that the AI system is directing the journey, rather than themselves, then the level of autonomy restriction should increase.

H4: Perceived autonomy restriction is positively associated with psychological reactance.

H6: Psychological reactance is negatively associated with customer journey satisfaction.

Reactance theory also suggests that there needs to be a boundary condition, and that is when freedom is restricted as being arbitrary or illegitimate rather than when the restricting party's reason for the restriction is understood and accepted. This logic is reinforced by research on trust, which shows that in digital settings, users' trust in the system and their compliance with the requirements for the system are affected by the perceived legitimacy of the system's requirements (Gefen et al., 2003). We therefore predict that such restrictions, ascribable to a legitimate security concern, will be re-interpreted as protective rather than control, although its association with reactance will be reduced, but not abolished.

H5: The positive relationship between perceived autonomy restriction and psychological reactance is weaker when security justification of friction is high than when it is low.

2.4 Journey Satisfaction and Continuance Intention

The overall satisfaction of the customer journey (the shopper's impression of the AI-enabled journey) is conceptualized as a proximal factor of effort-reward imbalance and of reactance, which are two different psychological pathways to the customer journey's dissatisfaction. Satisfaction is an established antecedent to continuance intention in technology-mediated service scenarios: When a shopper is satisfied with an AI experience she or he is more likely to continue, and reactance can also negatively influence continuance, even without affecting satisfaction.

H7: Customer journey satisfaction is positively associated with continuance intention.

3. Conceptual Model

The two theoretical pathways are combined in one path model (figure 1). The top route presents the Effort–Reward Imbalance route with Perceived Effort and Perceived Reward flowing into Effort–Reward Imbalance, impacting on Journey Satisfaction. The Psychological Reactance route (bottom) connects to the Psychological Reactance via the mediator of Security Justification of Friction and also indirectly to Journey Satisfaction. The shared proximal driver of Continuance Intention is Journey Satisfaction. The model does not view the two theories as competing, but rather complementary explanations: effort is tolerated when it's reciprocated, restriction is tolerated when it's justified. Together they define the circumstances in which AI-powered friction becomes friction and the circumstances in which it becomes friction plus value.Together they define when friction with AI becomes friction and when friction with AI becomes friction plus value..

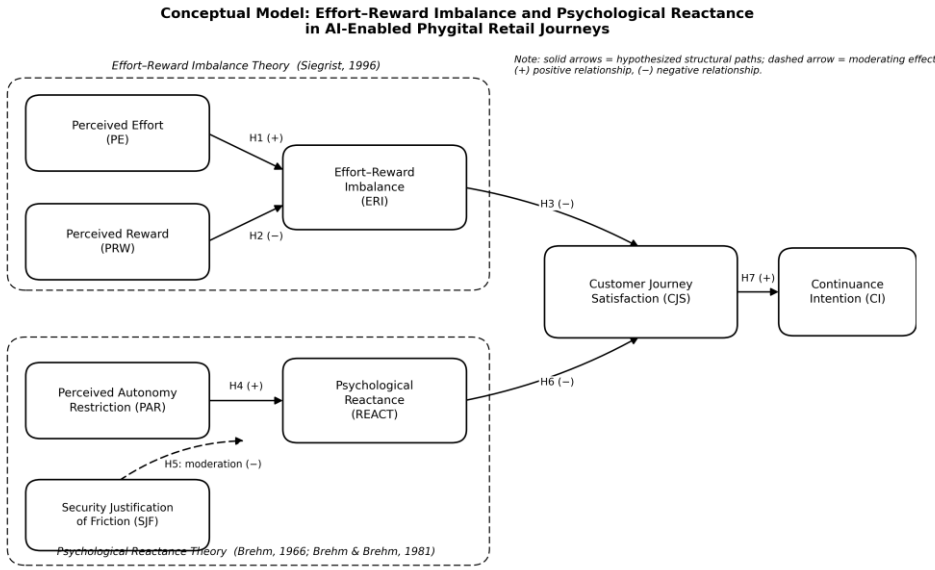


Figure 1. Conceptual model linking Effort–Reward Imbalance Theory and Psychological Reactance Theory to AI-enabled phygital retail journey outcomes.

4. Methodology

4.1 Research Design and Sample

A cross-sectional, quantitative survey design was used. Those who were eligible for the survey were 18 years or older and were customers of a retail format they defined as AI-enabled or "phygital" (uses self-checkout with computer-vision monitoring, biometric or app verification, or an in-store experience that is connected to the retailer's app). The data was collected online from the consumers in Delhi-NCR and other Metro and Non-Metro cities in India. A total of 342 questionnaires were received of which 31 (9.1%) were discarded due to incomplete responses or because they failed one of the attention-check items, leaving an analytic sample of N = 311. Demographic characteristics of the final sample are shown in Table 1.

4.2 Measures

All constructs were assessed using multi-item Likert-type scales (1 = strongly disagree and 5 = strongly agree), adapted from the effort–reward imbalance and psychological reactance literatures and adapted to the AI-enabled retail journeys. Perceived Effort (4 items) and Perceived Reward (4 items) operationalized the cost and gain components of the ERI theory, while Effort–Reward Imbalance (3 items) captured the perceived imbalance between effort and reward directly. Perceived Autonomy Restriction (4 items) and Psychological Reactance (4 items) operationalised the reactance route and Security Justification of Friction (3 items) measured the extent to which respondents agreed that the friction was a legitimate security rationale.

Customer Journey Satisfaction (4 items) and Continuance Intention (3 items) were the outcome measures. A single item control (familiarity with AI in retail 1-5) was also gathered. The coding scheme and full item wording are included in the item codebook that accompanies the data set.

4.3 Procedure

The questionnaire was sent online, preceded by a screening question and an informed consent statement and anonymity guarantee. The order of the items in each construct block was predetermined, and order effects were minimised by varying the order of the construct blocks presented. The average time it took to complete the median was around seven minutes.

4.4 Common Method Variance

Common method variance (CMV) is an issue since all constructs were self-reported in one questionnaire (Podsakoff et al., 2003). At the design stage, procedural remedies were used (anonymity, psychological separation of predictor and outcome blocks, reverse-worded attention checks). In addition, a Harman single-factor test also was applied: An unrotated principal-component analysis of all 29 items accounted for 17.5% of the total variance, which is below the 50% criterion considered to be indicative of a CMV problem, suggesting that common method variance is probably not responsible for the pattern of results.

4.5 Analytical Strategy

Internal consistency was assessed with Cronbach's alpha, and convergent validity with average variance extracted (AVE) and composite reliability (CR), following conventional thresholds (α and CR $\geq$ .70; AVE $\geq$ .50) (Fornell & Larcker, 1981; Nunnally, 1978). Discriminant validity was assessed by comparing the square root of each construct's AVE with its correlations with other constructs. Hypotheses were tested using correlation analysis and hierarchical ordinary least squares (OLS) regression on standardised composite (mean) construct scores a regression-based path-analytic approach appropriate for testing a decomposed structural model of this size. The moderation hypothesis (H5) was tested by entering a mean-centred interaction term.

5. Results

5.1 Sample Profile

Demographic profile of final sample (N = 311) is summarized in Table 1. The male population exceeded the female population in the sample (55.0%) and the highest age group consisted of 25-34 year olds (34.4%). Just over half (49.5%) had an undergraduate qualification, just over a third a postgraduate qualification (34.7%). The respondents were distributed almost evenly among the income brackets and 46.3% of the respondents lived in Delhi-NCR, followed by other metro cities (29.6%) and non-metro/tier-2–3 cities (24.1%). As per the eligibility screening, 100% of respondents had visited an AI enabled

phygital store within the last three months; 62.1% of respondents visited the store 3 or more times in the last three months.

Table 1. Demographic Profile of Respondents (N = 311)

Variable	Category	n	%
Age	25-34	107	34.4%
	18-24	75	24.1%
	35-44	55	17.7%
	45-54	50	16.1%
	55 and above	24	7.7%
Gender	Male	171	55.0%
	Female	138	44.4%
	Other / Prefer not to say	2	0.6%
Education	Undergraduate	154	49.5%
	Postgraduate	108	34.7%
	Up to Higher Secondary	29	9.3%
	Doctorate / Other	20	6.4%
Monthly Household Income (INR)	Rs.30,001-60,000	93	29.9%
	Rs.60,001-1,00,000	89	28.6%
	Above Rs.1,00,000	68	21.9%
	Below Rs.30,000	61	19.6%
Occupation	Salaried employee	158	50.8%
	Student	87	28.0%
	Self-employed / Business	51	16.4%
	Other	15	4.8%
Region	Delhi-NCR	144	46.3%
	Other metro city	92	29.6%
	Non-metro / Tier-2,3 city	75	24.1%
Visits to AI-enabled store (last 3 months)	3-5 times	129	41.5%
	1-2 times	118	37.9%
	6 or more times	64	20.6%

5.2 Reliability and Validity

Cronbach's alpha (0.70) and composite reliability (0.90) values were satisfactory for all eight constructs (range = .78–.84 and .90–.92 respectively), signifying good internal consistency. The mean variance extracted was between .70 and .79, well above the .50 threshold, thus indicating convergent validity. Discriminant validity was supported by the square root of AVE for each construct being greater than the inter-construct correlation for each construct with the other constructs (highest inter-construct correlation = .46, between Perceived Autonomy Restriction and Psychological Reactance, shown in parentheses on the diagonal in Table 4).

Table 2. Reliability and Convergent Validity

Construct	Items	Cronbach's α	CR	AVE
Perceived Effort (PE)	4	0.831	0.916	0.731
Perceived Reward (PRW)	4	0.840	0.921	0.745
Effort–Reward Imbalance (ERI)	3	0.800	0.917	0.788
Perceived Autonomy Restriction (PAR)	4	0.821	0.910	0.717
Psychological Reactance (REACT)	4	0.833	0.917	0.735
Security Justification of Friction (SJF)	3	0.783	0.909	0.769
Customer Journey Satisfaction (CJS)	4	0.811	0.905	0.704
Continuance Intention (CI)	3	0.792	0.913	0.778

5.3 Descriptive Statistics and Correlations

Moderately favourable, but not extreme evaluations of the overall AI-enabled journey are shown by the composite construct, which was evaluated at M = 3.31–3.35, SD = 0.77–0.83 (Table 3).

Table 3. Descriptive Statistics of Composite Construct Scores

Construct	M	SD	Min	Max
Perceived Effort (PE)	3.34	0.78	1.25	5.00
Perceived Reward (PRW)	3.34	0.79	1.00	5.00
Effort–Reward Imbalance (ERI)	3.31	0.82	1.00	5.00
Perceived Autonomy Restriction (PAR)	3.35	0.77	1.00	5.00
Psychological Reactance (REACT)	3.31	0.80	1.25	5.00
Security Justification of Friction (SJF)	3.32	0.79	1.00	5.00
Customer Journey Satisfaction (CJS)	3.32	0.77	1.25	5.00
Continuance Intention (CI)	3.31	0.83	1.00	5.00

Unsurprisingly, there was a positive correlation between Perceived Effort and Effort–Reward Imbalance ($r = .28$, $p < .01$), and a negative correlation between Perceived Reward and Effort–Reward Imbalance ($r = -.23$, $p < .01$). Perceived Autonomy Restriction was strongly negatively correlated with Psychological Reactance ($r = .46$, $p < .01$) and Security Justification of Friction was negatively correlated with Reactance ($r = -.32$, $p < .01$). The Effort–Reward Imbalance ($r = -.23$, $p < .01$) and Reactance ($r = -.28$, $p < .01$) were negatively related to the Journey Satisfaction, which was, in turn, positively related to the Continuance Intention ($r = .41$, $p < .01$).

Table 4. Correlation Matrix (Fornell–Larcker Discriminant Validity Table)

	PE	**PRW**	**ERI**	**PAR**	**REACT**	**SJF**	**CJS**	**CI**
PE	**(0.86)**							
PRW	0.14	**(0.86)**						
ERI	0.28	-0.23	**(0.89)**					
PAR	-0.05	-0.07	0.03	**(0.85)**				
REACT	-0.06	-0.05	0.03	0.46	**(0.86)**			
SJF	0.06	-0.00	-0.03	-0.21	-0.32	**(0.88)**		
CJS	-0.06	0.06	-0.23	-0.13	-0.28	0.11	**(0.84)**	
CI	0.07	0.08	-0.06	-0.16	-0.28	0.06	0.41	**(0.88)**

Note. Diagonal values in parentheses and bold are the square root of AVE. PE = Perceived Effort; PRW = Perceived Reward; ERI = Effort–Reward Imbalance; PAR = Perceived Autonomy Restriction; REACT = Psychological Reactance; SJF = Security Justification of Friction; CJS = Customer Journey Satisfaction; CI = Continuance Intention.

5.4 Hypothesis Testing

The findings of the four regression models to test H1–H7 are presented in Table 5.

The results for Model 1 (DV: Effort–Reward Imbalance) supported H1 (Perceived Effort was significant, positive predictor, $\beta = .32$, $t = 5.99$, $p < .001$) and H2 (Perceived Reward was significant, negative predictor, $\beta = -.28$, $t = -5.21$, $p < .001$) ($R^2 = .152$).

Model 2 (DV: Psychological Reactance) supported H4 as Perceived Autonomy Restriction was a strong positive predictor ($\beta = .41$, $t = 8.32$, $p < .001$). In keeping with the hypothesis, Security Justification of Friction was a significant negative predictor ($\beta = -.23$, $t = -4.70$, $p < .001$), and the Autonomy Restriction × Security Justification interaction term was significant and negative ($\beta = -.10$, $t = -2.00$, $p = .046$), meaning that the positive effect of autonomy restriction on reactance was weaker among respondents who perceived the friction as security-justified ($R^2 = .274$).

The results of Model 3 (DV: Customer Journey Satisfaction) indicated that both Effort–Reward Imbalance ($\beta = -.22$, $t = -4.08$, $p < .001$) and Psychological Reactance ($\beta = -.27$, $t = -5.03$, $p < .001$) were negative predictors, thus supporting both H3 and H6 ($R^2 = .123$).

For H7, Customer Journey Satisfaction was a significant positive predictor of Model 4 (DV: Continuance Intention) with $\beta = .36$, $t = 6.79$, $p < .001$. Psychological Reactance also had a significant direct negative effect on continuance intention beyond its indirect pathway through satisfaction ($\beta = -.18$, $t = -3.37$, $p < .001$) which "signifies that psychological Reactance could evoke an evaluative resistance to future use (dissatisfaction) and a more direct pathway of resistance ($R^2 = .197$).

Table 5. Structural Path Coefficients (Standardised)

Hyp.	Structural Path	β (std.)	t	p	Decision
H1	PE → ERI	0.317	5.99	< .001	Supported
H2	PRW → ERI	-0.276	-5.21	< .001	Supported
H4	PAR → REACT	0.414	8.32	< .001	Supported
	SJF → REACT	-0.234	-4.70	< .001	
H5	PAR × SJF → REACT (interaction)	-0.104	-2.00	0.046	Supported
H3	ERI → CJS	-0.218	-4.08	< .001	Supported
H6	REACT → CJS	-0.268	-5.03	< .001	Supported
H7	CJS → CI	0.360	6.79	< .001	Supported
	REACT → CI (direct)	-0.179	-3.37	< .001	

Table 5b. Model Fit Summary

Model	Dependent Variable	R^2	F-test p
Model 1	Effort–Reward Imbalance (ERI)	0.152	< .001
Model 2	Psychological Reactance (REACT)	0.274	< .001
Model 3	Customer Journey Satisfaction (CJS)	0.123	< .001
Model 4	Continuance Intention (CI)	0.197	< .001

All seven hypotheses were supported. Table 6 summarises the hypothesis-testing outcomes.

Table 6. Hypothesis Summary

Hyp.	Statement	Result
H1	Perceived effort is positively associated with effort–reward imbalance.	Supported
H2	Perceived reward is negatively associated with effort–reward imbalance.	Supported
H3	Effort–reward imbalance is negatively associated with journey satisfaction.	Supported
H4	Perceived autonomy restriction is positively associated with psychological reactance.	Supported
H5	Security justification of friction weakens the autonomy restriction → reactance link.	Supported
H6	Psychological reactance is negatively associated with journey satisfaction.	Supported
H7	Journey satisfaction is positively associated with continuance intention.	Supported

6. Discussion

The results validate the paper's core claim, namely that AI-induced friction in phygital retail is not necessarily bad, but rather its effects rely on the trade-off between effort and reward and whether the consumer is convinced of the restriction it creates is fair. Journey satisfaction is the point of convergence of two psychologically independent paths. The Effort–Reward Imbalance route reveals that consumers don't simply assess one part of the equation when it

comes to AI-powered verification and security measures – they assess them alongside the reward they're getting. As long as perceived reward (security assurance, useful personalisation) matches perceived effort, imbalance and dissatisfaction will be low, consistent with the reciprocity logic of ERI theory as used in the workplace (Siegrist, 1996; van Vegchel et al., 2005), and suggesting that this logic is applicable to consumer-oriented AI environments.

The Psychological Reactance route implies that friction is incurred in a different manner when it is perceived as an imposition on choice, rather than a cost–reward exchange. This is in line with the increasing amount of AI-marketing research that has documented reactance as a response to algorithmic systems that limit or veto consumer decisions (Longoni et al., 2019; Oh et al., 2025). What's novel is the moderating effect of security justification: If consumers recognize and accept the justification for a restriction, the same objective friction generates significantly less reactance. This finding expands on the "personalisation paradox" and the "algorithm aversion" bodies of literature by specifically marking a boundary condition in which perceived legitimacy of purpose is not perceived as aversive, but all constraints imposed on users by AI are not.

Importantly, reactance had an indirect effect on continuance intention via satisfaction, as well as a direct effect, indicating that repugnance of AI-related friction is not solely evaluative. The terms "satisfactory" and "disengage" can be interpreted as a single behaviour by some customers who are satisfied even as they avoid using specific AI elements that limit autonomy (such as not using AI recommendations, staying away from self-checkout lanes, or asking for assistance from humans).

These together make a new definition of the "frictionless commerce" goal. The effort–reward and autonomy-restriction paths suggest two independent design levers proportionate reward and transparent justification that can enable retailers to remove the friction they need for security, fraud prevention, or data governance without causing the satisfaction or loyalty drop and strain or resistance that result from removing it. It's not just about minimizing friction, it's about tuning it, in other words, it's about having a value function for friction.

7. Implications

7.1 Theoretical Implications

By applying the logic of effort–reward imbalance beyond its original application in an occupational stress context to the consumer context of the AI-enabled retail journey, this study proposes a new framework for understanding the effort–reward dynamic and how it shapes consumer evaluation of the security-focused, effortful actions embedded within the retail journey. It also contributes to the literature by introducing security justification as a novel, theory-consistent boundary condition for the autonomy-restriction–reactance

relationship in an AI context, lending empirical specificity to recent arguments in the literature that research should examine when, and not only if, algorithmic systems place a boundary on choice (Nokhiz & Ruwanpathirana, 2025; Oh et al., 2025). Lastly, the theories are integrated in a single model, showing that "cost" (effort–reward) and "control" (autonomy–reactance) are analytically distinct paths toward dissatisfaction, something that previous phygital-retail research, which has viewed friction as a monolithic concept, has failed to make explicit.

7.2 Managerial Implications

There are four practical implications for retailers and AI system designers.

Effort matches, visible, proportionate reward the more effort the more reward, and if it's visible to the shopper it's more likely to be perceived as balance than if it's not.

Tell rather than tell: When introducing a step, briefly and specifically communicate the reason for the step (e.g., "Verify for protection of your account").

Maintain some level of perceived control, wherever possible, such as providing an alternative path (assisted checkout) as well as a mandatory AI path, because it is the perceived control that is the heart of reactance theory, even if the underlying process cannot be avoided.

Some resistance behaviors do not always correlate with satisfaction scores, such as feature avoidance, opt-outs and escalation to human staff, so these also need to be followed up.

8. Limitations and Future Research

These conclusions are subject to a few limitations. The design is cross sectional and correlational, no causal direction of effects can be assumed among the modeled constructs and reverse or reciprocal relationships (e.g., when satisfaction is low, the retrospective report of effort is low) may not be excluded. All measures were self-reported and there was no serious common method problem as suggested by Harman's single-factor test, but this kind of test is not a substitute for other methods like a marker-variable design. The sample was recruited using convenience sampling on the internet and consisted of urban India, and care was taken with the generalisability of the findings from this sample to other cultural and economic settings; an issue that is of particular concern in respect of reactance and which previous studies indicated varies with cultural orientation towards autonomy. The study also applied regression-based path analysis on composite scores instead of a fully latent variable structural equation model, which would not fully account for measurement error, and a larger sample would enable more careful, simultaneous testing of the measurement and structural model, as well as formal tests of mediation and moderated mediation. The moderate variance explained for each endogenous

construct (12–27%) also suggests that other predictors, such as brand trust, prior negative experience with the technology, privacy concern, and technology readiness may have an influence and should be included in future models. Experimental testing of the model with artificial manipulation of AI-enabled friction and how easily it is perceived as security-justified is also recommended for future research, as are the further study of boundary conditions like the type of friction (biometric vs. OTP vs. consent prompts), which could vary in terms of how easily they are perceived as security-justified.

9. Conclusion

The default goal for retail tech has always been frictionless, but the AI systems that power the phygital experiences of today can't help but have some friction and this study suggests in some cases it's beneficial. The study, which combines two theories, Effort–Reward Imbalance theory and Psychological Reactance Theory, demonstrates that AI-induced friction negatively affects journey satisfaction and continuance intention when effort is greater than reward or when there is perceived lack of security justification for the friction but that proportional justice of reward and meaningful security justification buffer and significantly mitigate these effects. Where it applies to retailers building the future AI-powered store, it's not about removing friction but about optimizing it: align effort with visible payoff; communicate limitations instead of silently imposing them; and maintain a degree of consumer choice in an automated flow. With this approach, friction can become a friend to a great customer experience, not an enemy.

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