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The Impact of Sustainability-Driven and Artificial Intelligence-Based Personalisation on Customer Loyalty at South Asia-Based Airlines

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Abstract
The global aviation industry is rapidly switching to AI-based service systems, which leads to an important research question about the effectiveness of Western digital adoption frameworks in explaining the sustainable behaviour of distressed state-owned enterprises (SOEs) that operate in developing countries. Therefore, the aim of this study is to investigate the impact of sustainability-driven and AI-based personalisation on passenger loyalty at Pakistan International Airlines (PIA) while examining the role of digital trust and the impact of geocultural privacy issues on the relationship between them. The research is based on a survey consisting of a sample of 128 Pakistan International Airlines (PIA) passengers. The data analysis was conducted using Pearson bivariate correlation and hierarchical multiple regression methods in SPSS software. The findings indicate that passengers who perceive AI technology as beneficial experience higher levels of satisfaction with their travel experience. Digital trust functions as the mandatory partial mediator which transforms functional digital utility into repeat purchase intention, whereas higher privacy concerns produce a statistically significant negative moderating effect that establishes a geocultural Privacy Paradox specific to the South Asian market context. Conclusively, the study results support a combined TAM–Brand Trust theoretical model, which provides strategic recommendations for implementing AI-driven and sustainability-influenced personalisation methods. In terms of implications, the findings may influence policymakers in formulating policies aligned with the Sustainable Development Goals of 9, 11 and 12. The findings may act as a guide for other businesses in the transport industry to better navigate challenging and hostile environments.

Keywords: Artificial Intelligence; Commercial Airline Industry; Customer Loyalty; South Asia.

1. Introduction

Airline industries around the world are experiencing rapid digitalisation. Airlines are attempting to shift their business models away from legacy means of service delivery to automated-algorithm-focused, hyperpersonalized customer experiences [1]. Elite airlines like Emirates, Qatar Airways, and Etihad are implementing solutions powered by predictive analytics and machine learning algorithms to anticipate passenger expectations and provide proactive service recovery, moving passengers through each step of their digital journey effortlessly and consistently across all channels to instil brand loyalty [2]. Today, Airlines no longer depend on Frequent Flyer Programmes (FFPs) to retain passengers; hyperpersonalization of the passenger end-to-end journey experience, quality, flow, and congruency has taken precedence as the focal point of passenger retention [3, 4]. In fact, Artificial Intelligence (AI)-powered proactive service recovery has become table stakes in airline marketing; airlines preemptively warn customers of possible failures before they happen, find the problems before the customer knows there is a problem, and solve the problem before the passenger even notices [5, 6]. As a result of the increased liberalisation and route-commonization of international air travel, integrating digital solutions with the passenger journey is no longer considered an opportunity for competitive differentiation but a necessity for industry survival [7, 8].

The dynamic global landscape described above paints the backdrop for this study. Pakistan International Airlines (PIA) was one of the first commercial airlines to begin operations in Asia. However, over the last couple of decades, it has experienced a continual decline in both service quality and brand reputation [9]. Today, PIA is struggling to manage widening losses and an increasing debt burden while operating ageing machinery and dealing with outdated airport facilities. Systemic poor management leads to continual operational failures that alienate passengers and cause high attrition rates [10, 9]. PIA's endemic issues have disproportionately hindered the once-leading Asian airline in light of the rise of its digitally focused Middle Eastern competitors, who are now defining the customer service standard of the region with their hyper-personalised AI customer experiences [11, 12]. While repeat-fliers of PIA in the past may have felt some degree of allegiance to the brand due to nationalistic pride or because PIA was one of the only airlines providing direct international flights out of Pakistan, passengers today have outgrown this emotional connection. Digital solutions present in competing airlines are widening the expectation gap between passengers and PIA, causing even the former supporters to feel disconnected from the airline [13, 9]. PIA finds itself in a vicious cycle; its loyal passengers are kept with the airline through emotional scarcity, but these same passengers are at risk of disconnecting with the brand if the quality gap continues to drive a wide chasm between digital-passenger expectations and PIA's inability to modernise [14, 9]. This study was conducted with the pressing, applied question of whether properly implemented digital solutions can help slow PIA's downward trajectory and prevent loyal diaspora passengers from leaving PIA permanently [15, 9].

The practical importance of this question stems from understanding whether digital hyper-personalisation, driven by AI, can successfully pivot the brand's image to make up for physical experience deficiencies and plug a customer retention loophole [16, 17]. Comprehending how AI-powered digital personalisation affects passengers introduces substantial theoretical contributions to this simple question. There are two pervasive paradoxes that fly in the face of implementing personalisation initiatives that existing literature does not account for in domestic SOEs like PIA. First, in regard to the Brand Trust Paradox, existing literature shows that in order for new technologies to be accepted by consumers, preexisting confidence in the institution must be present [18]. PIA is an airline plagued by distrust as a State-Owned Enterprise (SOE); thus, passengers may be inclined to distrust the intentions behind PIA's data collection. This creates the possibility that, rather than increasing brand favorability, personalisation may actually hurt the brand if customers feel their privacy is being exploited. Second, the Privacy Paradox shows that while consumers desire deeply personalised experiences, they are hesitant to be monitored to deliver these expected experiences [19]. Western ideologies fail to translate these realities into the paradoxes present in an environment like PIA, operating within a weak Pakistani state. This research is imperative for practitioners dealing with failing SOEs and theorists who study the limitations of technology acceptance.

What makes this study novel is the fact that it seeks to fill two substantial voids in the literature. Aviation literature is severely biased toward studying AI implementation at well-funded North American and European airlines. This creates a gap in understanding the passenger

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psychology of one of the world's largest yet operationally complicated aviation markets: South Asia. Additionally, while prior studies look into how AI can help already successful brands grow, this study looks at how AI can help as a direct brand remediation strategy for flailing, underfunded incumbent SOEs. Combining the TAM, Brand Trust Theory and the Triple Bottom Line (TBL) into a unified framework and testing it against the real-world scenario at PIA, this study breaks away from merely descriptive, qualitative studies and aims to produce novel, data-backed findings on whether digital personalisation can be used as an institutional brand-recovery strategy. Finally, there appears to be a dearth of literature investigating the role of sustainability-aligned (i.e., SDG 9, 11 and 12) practices in influencing consumer behaviour and loyalty, especially in the context of South Asia-based commercial airlines. Therefore, the purpose of this study is to test the effects of sustainability-driven and AI-powered digital personalisation on customer loyalty at Pakistan International Airlines (PIA). The purpose of this study will be underpinned by the following research objectives:

RO1: To review the current body of literature to develop and test a sustainability-driven, consumer-perspective-based, and AI-diffusion-related theoretical framework unique to this study, therefore also leading to an original theoretical contribution.

RO2: To conduct empirical research involving PIA customers to gain insights into the impact of sustainability and AI-powered digital personalisation on customer loyalty in the context of the South Asian airline industry, which is not reflected in the current body of literature.

The structure of the remainder of the paper will consist of a literature review conducted in Section 2. The methodology will be outlined in Section 3. The findings will be presented and analysed in Section 4. An original contribution to knowledge will be established in the discussion in Section 5. Finally, the paper will conclude with Section 6, which will establish the key findings of the research, implications, limitations and recommendations related to the study.

2. Literature Review

2.1 The Role of AI in Business

AI in business has moved from merely optimising backend processes to becoming a key part of the front-end customer experience [20]. [20]'s framework on the Feeling Economy explains that as AI takes over the analytic and data-heavy computation, humans are freeing up their time for empathetic and customer-facing roles requiring an ability to display emotions that machines currently cannot. Studies like [21], [22] and [5] extend the view, stating that AI can help proactively prevent the negative aspects of a customer experience by predicting where a service failure is going to happen by analysing past data, thus making AI not a passive means for cost savings but an active predictor that builds competitive advantage through its ability to silently fix problems before they occur.

However, this positive commercial vision is challenged by research on the Privacy Paradox, which states that the public is contradictory in that they desire hyper-personalised experiences but resent the surveillance technology needed to provide these. While firms push for widespread data mining and granular algorithmic segmentation to maximise the benefits of a loyalty programme, too much of this can actually alienate customers, potentially in ways that particularly harm airlines in the target segment [23]. This suggests that capability isn't a sufficient condition-AI can actively drive customers away if used inappropriately, according to their own comfort levels with the necessary surveillance technology.

2.2 Understanding Customer Loyalty Metrics

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The concept of customer loyalty has shifted from models of structural dependence on switching costs to models centred on customer experience. The foundational [24] model relied on structural retention mechanisms based on 'financial sunk costs,' or at least the disincentives of forfeiting accrued Frequent Flyer Program miles, which created the idea of a 'loyal' customer as someone with high switching costs [24]. These 'hard' or structural incentives for loyalty are increasingly overshadowed by customer relationship management, and the argument that in a commoditised world, the 'digital' journey is everything, especially given how easy competitors are to mimic in terms of loyalty program incentives [4]. A 'loyal customer' is now a psychologically attached customer based on overall experiences across the whole journey, the physical and the digital.

Research studies like [25] and [26] empirically support this view, with [27] finding that AI-driven personalisation is the single strongest predictor of repeat purchasing behaviour. [28] add nuance to this finding that AI-driven loyalty is stronger when mediated by institutional trust between the customer and the technology provider. This point is crucial in light of legacy carriers with problematic institutional reputations. AI alone cannot overcome any such trust deficit; it will act through that deficit. Therefore, building trust should be a prerequisite to developing an effective digital loyalty strategy.

2.3 The Global Airline Industry

Commoditisation of many of the previous distinguishing characteristics, such as routes, physical product and FFP loyalty benefits, means that legacy carriers are now fighting the war on the digital battlefield and for the overall customer experience. [29] argued that the openness of skies and competition from LCCs meant that routings became uncompetitive, and cabin physical standards became a commodity that could no longer be used to compete. [30] showed evidence that Gulf Air is increasingly winning business through sophisticated use of AI and thus generating the required hyper-personalised passenger experiences, shifting from a physical to a digital competitive battle.

However, an important nuance to be understood within the airline industry is the role of AI in generating revenue. While [31] argues that AI can be used to automate revenue maximisation through dynamic pricing and granular segmentation, this optimism has to be balanced with what happened at several North American carriers in 2018 when customer service chatbots produced a range of errors and caused significant brand damage that took years of exemplary service to undo [32]. The argument here is that while AI can generate new revenue streams, if not monitored, these can be completely undone when customer trust and brand reputation are damaged by poor-quality service generated by an AI algorithm that fails when its capabilities exceed the bounds of what it was originally programmed to do.

2.4 Overview of Pakistan International Airlines

PIA is an interesting and paradoxical institutional case-the organisation has a base of customers that are incredibly loyal on a 'feeling' level, but the organisation is systematically losing customers on a transactional and practical level. [13] note the remarkable loyalty from the Pakistani Diaspora, grounded in cultural affiliation, national pride, and a pragmatic need for direct flights to Pakistan. This built-in loyalty can provide a buffer against competitors. However, [10] uses financial data to show that these structural advantages are eroding as the organisation suffers from operational and financial failures, suggesting that nationalistic sentiment is a consumable resource and ultimately unable to compensate for operational and structural failures on an ongoing basis.

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PIA's lack of digital capabilities has further exacerbated its physical product failures to the point where the difference in digital quality is itself a key factor influencing passenger decision-making. [33] noted that service tangibility and frontline staff were issues. [34] demonstrates that these legacy weaknesses are now manifesting as digital weaknesses, with PIA being non-existent in the space of AI-driven capabilities, automated rebooking, or proactive customer service, meaning that PIA is consistently losing passengers to technically superior Gulf carriers. Over 20 years, this physical-to-digital decline of capability has reinforced each other, making it hard for PIA to regain its hold on the market, especially with premium passengers.

2.5 Theoretical Overview

The Technology Acceptance Model (TAM), conceptualised by [35], still reigns as the paradigm through which consumer adoption decisions for technologies are explained, arguing that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) represent the main drivers of purchase intention. The validity and current applicability in the aviation context have been validated by [27], who concluded that easy-to-use AI personalisation services, such as automatic seat upgrades, dynamic pricing suggestions, and contextual travel guidance, are directly related to and significant for customer satisfaction and engagement. The problem with TAM, however, is its assumption of consumer trust neutrality-an idea which is intuitively invalid in the case of financially troubled SOEs, whose customers already suffer from the feeling of insecurity of their physical and technological infrastructure, let alone the privacy implications of well-managed personal data by an institution that they already distrust for providing such basic services properly [10].

Brand Trust Theory, as defined comprehensively by [18], fills this gap and posits two necessary components for enduring emotional loyalty: Brand Reliability (functional dimension), which concerns the capacity of the brand to consistently perform its service as expected, and Brand Intentions (ethical dimension), which relates to the belief that the brand would not intentionally harm or exploit the consumer relationship. Both components have been found lacking for PIA. Where consumers hold the institutional view of the airline to be institutionally unreliable and professionally inept, they will avoid any technologically driven interactions, no matter how user-friendly or value-oriented they may be made out to be.

The bridging link between the aforementioned concepts is e-commerce research by [36], which establishes that, under conditions of uncertainty, initial online trust is primarily responsible for alleviating risk. Customers new to an online transaction site use the institutional trust cues to make sense of and feel safe about interacting with it. A combination of TAM, Brand Trust Theory, and [36]. The digital trust study leads to the conceptual model of this study, where digital trust is seen as the obligatory mediating variable between perceived AI utility (PU, PEOU) and repurchase intention. The rationale is that functional AI features can't automatically override the existing feeling of distrust toward the brand; only after trust is established in the system can functional advantages translate into commercial value and loyalty. Additionally, the study will be looking to map the variables against the Sustainable Development Goals, which may be appropriate via the Triple Bottom Line (TBL) theory, which is widely considered the most prominent theory on sustainability. The TBL consists of Profit (Economic), People (Social) and Planet (Environmental).

Profit (Economic) involves traditional metrics for corporate profit. Contributing examples: direct economic profit, number of jobs created, economic stability. People (Social) involves metrics that score how well the company takes care of its social responsibilities. Contributing examples: fair wages, local community impact, diversity and inclusion, employee

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happiness. Planet (Environmental) shows how much of a carbon footprint a company has, e.g., resource use, pollution, emission control, and use of renewable energy [46, 47, 48].

2.6 Review of related studies

The existing body of empirical studies is critically evaluated to reveal two significant gaps in knowledge, which this study aims to fill. The first is geo-cultural; much of the AI adoption and sustainability practices-related literature in aviation is based on Western, high-trust, digitally mature environments, with existing regulations [5, 32]. Extrapolating these findings to South Asian contexts is academically inappropriate. Existing cross-cultural studies have demonstrated that customers in high-uncertainty-avoidance cultures have systematically different reactions to sustainability, AI surveillance and value data sovereignty, human intervention, and system transparency over the convenience offered by automation. Consequently, the perception of Pakistani passengers towards AI data collection and sustainability is substantially different to the one reflected by Western passengers in existing research.

The second gap is contextual; existing empirical research focuses primarily on the deployment of AI to enhance the operations of already established and highly capitalised carriers, such as those in the Gulf region or Western legacy airlines [30, 31]. However, there is an obvious void of any empirically tested research studying AI as a brand-recovery tool for an institutionally tarnished brand in a poor, emerging market. Although [31] models the AI features as enhancing operational efficiency, there is no research explaining whether the public will actually trust and adopt those digital interventions provided by an airline with PIA's history of failure. This research seeks to fill that niche.

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2.7 Synthesis of Findings and Hypotheses

In conclusion, the literature review established that in an increasingly commoditised airline market, digital agility is no longer a choice but a requirement, and that dominant research paradigms require adaptation to become applicable in the context of a distressed emerging-market SOE. All identified themes-The Feeling Economy's displacement of analytical capacity towards AI, the Privacy Paradox limiting personalisation in the context of low trust, patriotism's erosion as a brand-loyalty driver through digital inadequacy, TAM's failure to account for institutional distrust - converge toward establishing the necessity of the hybrid framework applied in this study, in which Digital Trust serves as a critical mediator to behavioural loyalty and sustainability. The following hypotheses will be subjected to quantitative validation:

H1: A positive relationship exists between AI Perceived Usefulness and Customer Satisfaction.

H2: Digital Trust positively mediates the relationship between AI Personalisation and Repeat Purchase Intention.

H3: Privacy Concerns negatively moderate the impact of AI benefits on Customer Loyalty.

3. Materials and Methods

3.1 Research Design

This study follows a deductive approach where the hypotheses formulated based on the theory are tested against the data. A deductive method was chosen because the aim of this research is not to generate new theories but rather to critically test and investigate how established Western theoretical models, TAM and Brand Trust Theory, work within a different context, a geoculturally and institutionally disparate domain. A deductive method is useful here

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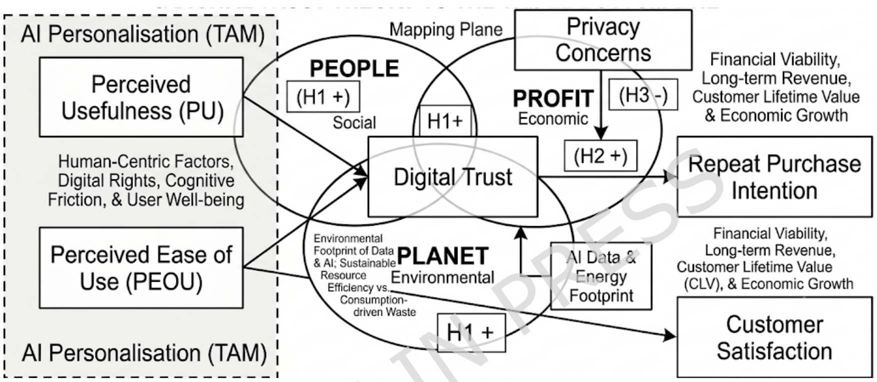
because it allows for structured testing and direct correlation between a priori theoretically-determined propositions and statistically analysed empirical data [37].

3.2 Measures

The study's framework combines the functional elements within TAM-Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as the independent variables that shape functional adoption, Digital Trust as the mediator of their relationship to loyalty, and Loyalty (Repeat Purchase Intention) as the dependent variable. Privacy concerns are hypothesised as the moderating variable, potentially attenuating the relationship between AI benefits and loyalty outcomes, directly incorporating and overriding TAM's trust-neutrality to the study's needs in a strained, state-owned enterprise (SOE) context. Additionally, all these variables are mapped against the Triple Bottom Line framework, which has been incorporated to address the sustainability element of this study.

Figure 1: Hybrid Theoretical Framework Combining TAM, Brand Trust Theory and Triple Bottom Line



The development of the conceptual framework illustrated in Figure 1 has been informed by the key findings from Section 2. This has also led to the fulfilment of RO1. As illustrated in Figure 1, the framework represents how AI Personalisation impacts customer outcomes, repurchase intention and customer satisfaction through the mediator digital trust (DT), but is moderated by privacy concerns (PC). The independent variables (IVs) are PU and PEOU, which act as the backbone for AI Personalisation. The DT mediates, or carries the effect of, the IVs to the final outcome. The moderator PC moderates, or weakens, an existing relationship. Lastly, the dependent variables (DVs) symbolise the outcomes of the study.

H1+ indicates that AI personalisation will have a positive effect on trust and satisfaction. More specifically, H1+ indicates that PEOU has a direct effect on customer satisfaction (CSAT). Similarly, PU and PEOU directly impact DT. Moving on, H2+ shows that DT is expected to have a direct and positive relationship with repeat purchase intention (RPI). Meaning that if a customer has more trust in the brand, they will be more likely to make a return purchase. Lastly, H3 indicates that PC will have a negative moderating effect on the relationship between DT and RPI. AI Personalisation creates DT, which leads to RPI. This last relationship is weakened if PCs are present. At the same time, Perceived Ease of Use creates CSAT directly.

Items to measure each construct were taken and modified from previous scales that have been developed and utilised in technology adoption, information privacy, and e-commerce research studies. Items to measure PU and PEOU were adopted from [35]. Digital Trust measurement items were adopted from [38]. Privacy Concerns scales were adopted from [39] Internet Users' Information Privacy Concerns (IUIPC) scales. Items that were used to measure

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the user outcomes of Customer Satisfaction and Repeat Purchase Intention were adopted from [40].

In terms of the Triple Bottom Line (TBL) in Figure 1, 'People (Social)' addresses people-centric aspects, digital rights, cognitive friction, and well-being. 'Planet (Environmental)' focuses on the environmental impact of datacenters/AI and digital solutions. Computing resource efficiency vs consumption/resource hoarding generates electronic/electricity waste. 'Profit (Economic)' looks at revenue, long-term monetisation, customer lifetime value, and growth.

Therefore, based on the conceptual framework, the hypotheses are interpreted in the following way.

H1: A positive relationship exists between AI Perceived Usefulness and Customer Satisfaction.

According to TAM's fundamental principle, the perceived usefulness of an AI personalisation tool will directly decrease mental effort/exertion and time for the customer and allow them to find personalised solutions. This will meet or exceed their performance expectancy, resulting in Customer Satisfaction.

According to TBL's components, Expansion (Profit & People) and Economic (Profit), perceived usefulness fuels utility. If an AI tool efficiently leads customers to the appropriate sustainable products/services they were looking for, their satisfaction will create brand stickiness and decrease Customer Acquisition Cost (CAC) while increasing Lifetime Value (LTV).

According to the Social (People) component, perceived usefulness should not benefit the company alone. If the AI allowed users to make more ethical, informed, or healthier decisions with little effort, customers would be satisfied by a valuable user experience not fueled by addictive and manipulative algorithmic incentives.

H2: Digital Trust positively mediates the relationship between AI Personalisation and Repeat Purchase Intention.

As per the core mechanism (Mediation), AI Personalisation requires a large flow of information going back and forth. The higher-quality, personalised information the AI provides to the consumer, the more the customer will feel understood. Building Digital Trust. This trust becomes the psychological currency; a customer will not make a Repeat Purchase Intention if they do not believe that the system will continue to provide value and protect their information ethically in the long run. Looking at it from the TBL Expansion (Profit & Corporate Governance), socially (People), and economically (Profit), digital trust is currency. Sure, personalisation can create a spark, but Digital Trust is what keeps the fire going by turning one-time buyers into repeat buyers (Repurchase Intention).

Pointing back at Social/Ethical (People), this mediation is demonstrating that you cannot get around trust with high-level personalisation. Trust for social sustainability in the long term means that AI must be transparent about how it operates. When a customer understands hyper-accurate personalisation is crossing the line into manipulation, the mediation is shattered-trust drops, intention to purchase again diminishes.

H3: Privacy Concerns negatively moderate the impact of AI benefits on Customer Loyalty.

The Core Mechanism (Moderation) depicts the well-known "Privacy Paradox." The typically positive aspects of AI (reflected in extremely high Perceived Usefulness & Ease of Use scores) lead to enduring Customer Loyalty. Privacy Concerns serve as a harsh damper/filter (negative moderator). With high privacy concerns, the impact of those AI positives on Loyalty decreases dramatically as fear of being taken advantage of supersedes the AI's convenience.

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Social (People) pillar of TBL Expansion (Planet, People & Profit), which focuses on data privacy, is a basic human right. Elevated privacy concerns demonstrate that the brand's "People" bottom line is broken. Should people feel as if their data is being unfairly exploited, any loyalty created by leveraging that convenience will be met with psychological unsustainability.

Finally, from an Environmental/Systems Lens (Planet/ Ecosystem). One can not have a sustainably happy ecosystem if trust is not part of the cycle. If a firm utilises AI to help produce "Planet-friendly" decisions, but infringes on data privacy to encourage those decisions, many consumers view this as a type of "digital greenwashing." The negative moderation of privacy concerns washes out the brand's efforts to produce loyal, planet-conscious customers.

3.3 Data Collection Method

The strategy is that of a mono-method quantitative survey. This approach to the survey methodology allows for standardisation across participants and a comparison between participants, as well as a method that can measure the relation between theorised variables statistically at an appropriate level to enable generalised conclusions [41]. Although alternative strategies such as qualitative case study or interview research were considered, they were rejected on methodological grounds. While interviews may provide in-depth richness, limitations such as the limited sample size and the potential for interviewer bias make qualitative interviews unsuitable for hypothesis testing at an appropriate statistical level.

Primary data was collected by using an online structured questionnaire based on Microsoft Forms. The questions on technology adoption and loyalty to the airline were based on five-point Likert scale items measuring agreeableness/disagreeableness. Items to measure the constructs were based on previous, valid measures from TAM and digital trust literature. Data were collected from two different travel-purpose categories: Business/Corporate travellers and Leisure/Religious travellers, by stratified random sampling so that these different segments were represented proportionately within the population. Instead of convenience sampling, a random sampling method was chosen due to the potential for bias, which often disproportionately represents younger, urban, tech-savvy users of air travel in an SOE context [42]. Data were collected from customers who have flown PIA's international routes in the previous 12 months and used PIA's digital platforms.

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3.4 Data Analysis Method

SPSS was used to conduct quantitative analyses of data using a multi-stage, inferential approach. The internal consistency of all Likert-scaled constructs was initially evaluated using Cronbach's Alpha, using a reliability threshold of .70 [43]. Pearson bivariate correlation then established the strength and direction of the association for H1, before performing a two-block hierarchical multiple regression for assessing the mediation effect (H2), using the significance of and increase in the R of each step (R) as indicators of the extent of mediation. A second regression was performed in order to test the moderating effects (H3) by including a mean-centred interaction variable (AI Personalisation Privacy Concerns). Multivariate analytical techniques were chosen due to the complex and multifaceted structure of the hypothesised variables and the fact that simple descriptive analysis of the data would be insufficient to reach and test hypotheses at the required level of certainty [44].

Research was undertaken following full compliance with Ulster University Research Ethics Committee guidelines, requiring institutional approval before commencing any data collection. Specific safeguards implemented included a mandatory, tick-box digital informed consent before participants could access the questionnaire, full anonymisation and lack of personal, political or professional identifier data (e.g., passport number, names), and all files to

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be stored securely on password-protected academic drives to which only the researcher had access. These were of particular importance in this study, where sensitive, potentially critical opinions were solicited on a major state-owned company that is subject to extensive governmental and business oversight.

4. Results

The result of thorough demographic screening of 150 initially collected surveys based on informed consent, international travelling experience within one year prior to the surveying period, and digital platform use was N = 128 survey participants. The number of survey samples obtained can already surpass the minimum sample size that should be collected, as suggested by [44]. The demographic profile of respondents is given in Table 1.

Table 1

Demographic Characteristics of the Sample

Demographic Variable	Category	Frequency (n)	Percentage (%)
Primary Travel Purpose	Business / Corporate Travel	64	50.0
	Leisure / Visiting Family & Friends	46	35.9
	Religious Travel (Umrah / Hajj)	18	14.1
Age Group	18–24	12	9.4
	25–34	48	37.5
	35–44	41	32.0
	45–54	18	14.1
	55+	9	7.0

Note. N = 128.

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As shown in Table 1, business/corporate travel was identified as the most common travel purpose, and the 25-34 and 35-44 age groups were the most common. The breakdown of travel purposes amongst respondents is illustrated in Figure 2.

Figure 2: Passenger Stratification by Travel Purpose

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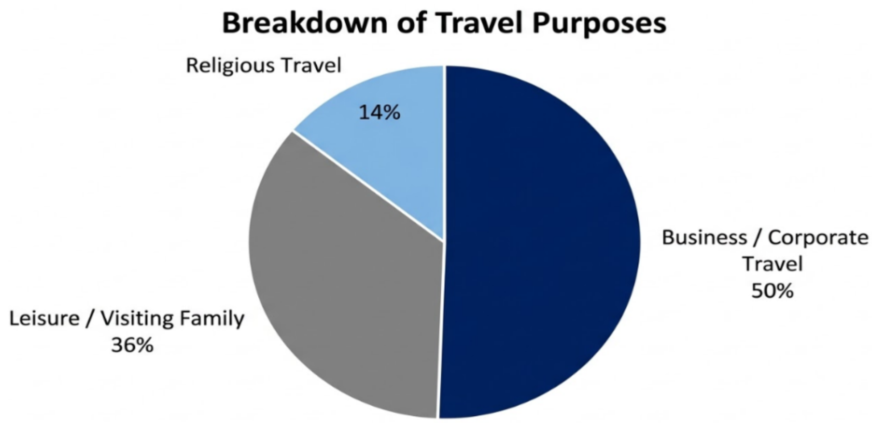

As illustrated in Figure 2, there was an interesting distribution of the strata according to commercial purposes, being 50.0% business/corporate (n=64), 35.9% leisure/family visiting (n=46), and 14.1% religious travel (n=18). The latter makes the distribution very strategically important, considering that business travellers are high-value customers in terms of digital service efficiency and reliability; at the same time, leisure and religious travellers make up the bulk of customers for PIA as far as its diaspora and pilgrim routes are concerned. Age-wise, the sample is dominated by individuals aged 25-44 years (69.5%), representing economically active and digitally literate clients who understand the service-quality difference between PIA and its Gulf competitors very well. The above-mentioned demographic is also highly sensitive to competition. In order to perform inferential analysis, all of the measurement scales were tested for internal consistency using Cronbach's Alpha test, with [43]'s criterion of $\alpha \geq .70$ being applied. The reliability statistics are provided in Table 2.

Table 2

Reliability Analysis of Measurement Scales

Construct	No. of Items	Cronbach's α	Consistency Rating
AI Personalisation (PU & PEOU)	5	.757	Acceptable / Good
Digital Trust	3	.828	Good
Privacy Concerns	2	.825	Good
Customer Loyalty / Satisfaction	4	.824	Good

Note. Cronbach's α values are reported to three decimal places per standard conventions.

As shown in Table 2, the reliability coefficient for all the constructs is greater than the $\alpha \geq .70$ requirement, thereby guaranteeing sufficient internal reliability across all measures. The reliability coefficients of the AI Personalisation construct ($\alpha = .757$), the Digital Trust Scale ($\alpha = .828$), the Privacy Concerns construct ($\alpha = .825$), and the Customer Loyalty/Satisfaction

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construct (α = .824) provide adequate validation of the survey measurement, thus justifying the subsequent composite mean calculation and the following multivariate regression analysis.

H1: There is a positive relationship between AI Perceived Usefulness and Customer Satisfaction.

The bivariate correlation analysis of the composite AI Perceived Usefulness measure and Customer Satisfaction measure gave r = .610 (p = .000, two-tailed), thus demonstrating a significant positive linear relationship between the variables. The Pearson Correlation Matrix for H1 is provided in Table 3.

Table 3

Correlation Matrix for AI Perceived Usefulness and Customer Satisfaction

Variable	1	2
1. AI Perceived Usefulness	—	
2. Customer Satisfaction	.610**	—

Note. N = 128.

** p < .01 (2-tailed).

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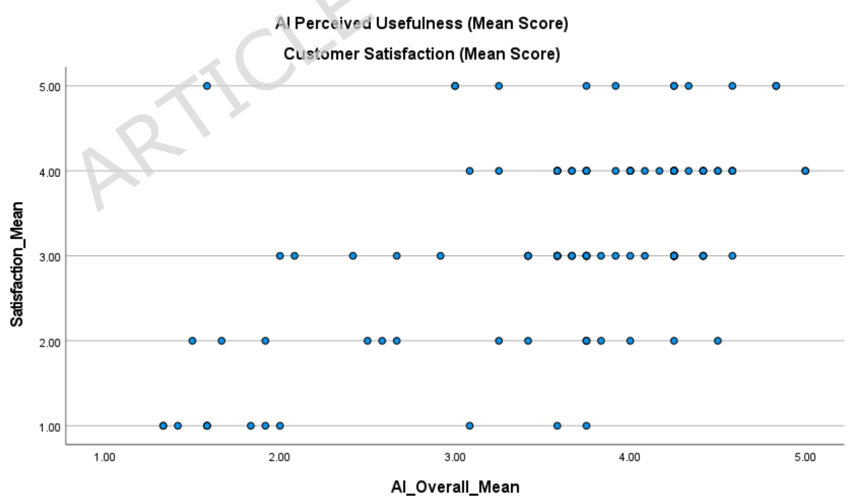
The relationship between AI usefulness and Customer satisfaction is illustrated in Figure 3.

Figure 3: Scatter Plot of AI Usefulness vs Customer Satisfaction



As demonstrated in Table 3 and Figure 3, the value of the coefficient (r = .610) shows that if passengers perceive PIA's use of digital technology as operationally useful due to automation in flight bookings, disruption warnings, and seat arrangements, then these individuals have correspondingly high overall levels of satisfaction with the airline. More importantly, it shows that this relationship holds irrespective of how well the PIA performs its physical operational tasks. This finding demonstrates that digital utility has the potential to work as a stand-alone satisfaction driver despite operating under conditions of severe distress.

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In line with Economic (Profit) and Expansion (Profit & People), discovering that digital utility is an independent driver illustrates that digital utility supercharges utility directly and independently of offline turmoil. This establishes that pouring money into intensely useful AI is a viable way to buy brand stickiness, suppress Customer Acquisition Cost (CAC), and defend Lifetime Value (LTV) if your operations start to falter.

In line with Social (People), because the dopamine hit is coming from direct, task-based utility, it can establish a user experience based on actual customer empowerment and lower cognitive load instead of dopamine-manipulative loops. Therefore, H1 has been supported.

H2: Digital Trust mediates the association between AI Personalisation and Repeat Purchase Intention.

Hierarchical Multiple Regression analysis was used for testing H2. Block 1 consists of one predictor, which is AI Personalisation, predicting Customer Loyalty. Block 2 has two predictors: AI Personalisation and Digital Trust. The Hierarchical Multiple Regression Analysis for H2 is provided in Table 4.

Table 4

Hierarchical Regression Analysis for the Mediating Effect of Digital Trust

Predictor Variables	**Model 1 (Std. β)**	**Model 2 (Std. β)**
Block 1: AI Personalisation	.773***	.485***
Block 2: Digital Trust	—	.406***
R^2	.598	.679
Adjusted R^2	.595	.674
R^2 Change	.598	.082
F-Change	187.226***	31.835***

Note. Std. β = Standardised Beta.

*** $p < .001$.

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The mediation model consisting of digital trust, technology adoption and loyalty is illustrated in Figure 4.

Figure 4: Mediation model demonstrating Digital Trust as the necessary bridge between technology adoption and loyalty.

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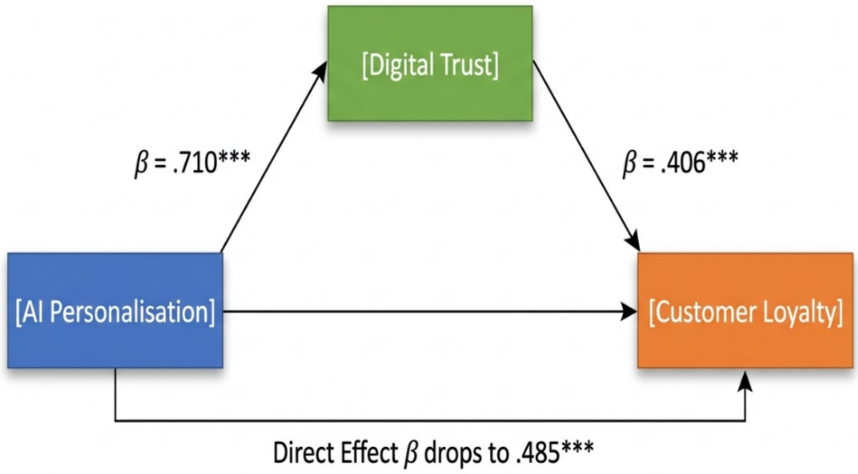

As shown in Table 4 and Figure 4, incorporation of Digital Trust into Block 2 led to a statistically significant improvement in the explanatory value of the model ($\Delta R^2 = .082$, F-change = 31.835, $p < .001$), suggesting that the trust component adds 8.2% more variance explained for the loyalty measure than the utility of AI by itself. More specifically, the AI Personalisation standardised regression coefficient decreased from $\beta = .773$ (Model 1) to $\beta = .485$ (Model 2), after the introduction of trust, whereas Digital Trust itself was found to be a strongly significant predictor of loyalty ($\beta = .406$, $p < .001$). Coefficient attenuation combined with retained statistical significance is a clear case of partial mediation: the AI-to-loyalty association remains significant, but digital trust emerges as an inevitable amplifier in the equation, without which technological investment will fall short of its financial goal.

According to Economic & Corporate Governance (Profit), decreasing the effect of AI Personalisation (β decreases from 0.773 to 0.485) mathematically demonstrates that personalisation by itself is only a depreciating value. Without Digital Trust as the "required multiplier," investments in technology will never meet their monetisation expectations. Trust is established as the true financial currency, which transforms singular transactions into repeat buyers.

According to Social/ Ethical (People), this partial mediation factually proves that businesses will not be able to substitute building an ethical data relationship with customers by simply purchasing shinier technology. Since trust is a necessary psychological ingredient, any customisation that violates a consumer's sense of transparency or manipulation will break this mediating cycle, eliminating long-term social impact and purchase intent. Therefore, H2 has been supported (Partial Mediation).

H3: Privacy Concerns negatively moderate the effect of AI benefits on Customer Loyalty.

Moderation was tested by first computing a mean-centred interaction term (AI Personalisation × Privacy Concerns) and then entering it in Block 2 of a hierarchical regression analysis with Customer Loyalty as the dependent variable. Mean-centring was applied to reduce multicollinearity between predictor variables and the interaction term. The results for the hierarchical multiple regression analysis for H3 are provided in Table 5.

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Table 5

Hierarchical Regression Analysis for the Moderating Effect of Privacy Concerns

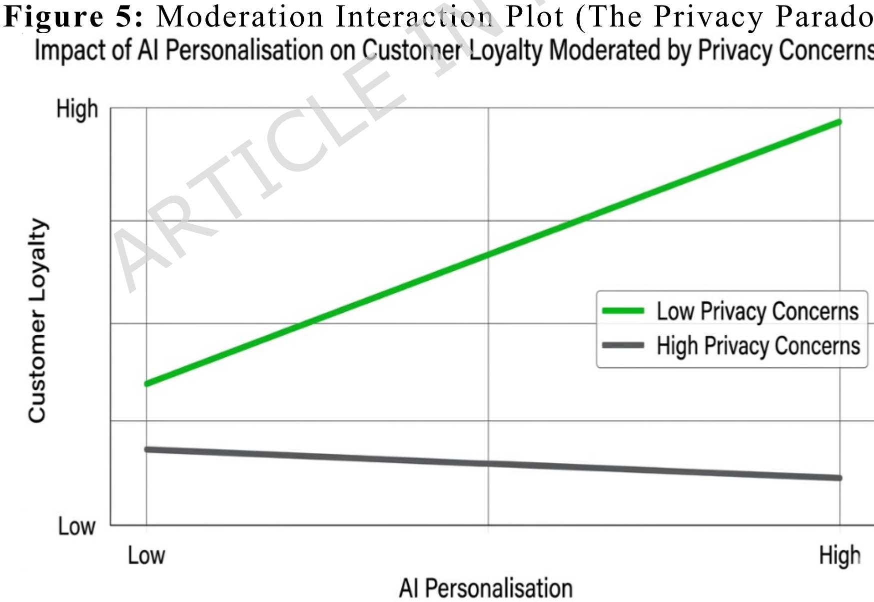
Predictor Variables	Model 1 (Std. β)	Model 2 (Std. β)
Block 1: AI Personalisation	.838***	.187*
Block 1: Privacy Concerns	.080	.041
Block 2: AI × Privacy Interaction	—	-.717*
R^2	.603	.617
R^2 Change	.603	.014
F-Change	94.963***	4.624*

Note. Std. β = Standardised Beta. Non-significant values are indicated by the absence of asterisks.

* p < .05. *** p < .001.

The privacy paradox involving customer loyalty and AI personalisation is illustrated in Figure 5.

Figure 5: Moderation Interaction Plot (The Privacy Paradox)



As indicated in Table 5 and Figure 5, there was a statistically significant interaction effect (β = -.717, p = .033), indicating that privacy concern negatively moderates the relationship between AI and loyalty. The stronger the passengers' fears of being surveilled by the airline, the weaker the positive relationship between AI usefulness and repurchase intent. Thus, the results provide an operational example of the Privacy Paradox in the current study context; that is, passengers who stand to gain from personalised algorithmic assistance actively disassociate themselves from the airline when such assistance requires the extraction of their data without any

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control on their part. It is interesting to note that privacy concern on its own does not appear to affect loyalty in either of the two blocks (β = .080, ns).

For Social (People), these results present a clear behavioural corroboration of the Privacy Paradox. Travellers who desire personalisation want it on their own terms. If an airline mines their data and doesn't afford them agency over it, they will take extreme measures to disconnect from the brand. Privacy infringement disrupts the "People" bottom line enough to psychologically offset any convenience the AI may provide.

From an Environmental/Systems Lens (Planet/ Ecosystem), a steep negative interaction slope (β=-0.717) indicates that if privacy is breached, the system no longer trusts the brand to look out for its best interests. If a corporation deploys AI to nudge or provide consumers with planet-friendly mobility options but violates their data privacy in the process, consumers perceive the system as digital greenwashing. The negative moderating effect taxes the brand enough to make its ecosystem ambitions unsustainable. Therefore, H3 has been confirmed. The measurement items of the variables are given in Table 6.

Table 6

Reliability Analysis of Measurements and Scales

Variable/Construct	Number of Measurement Items	Cronbach's α	Consistency Rating
AI Personalisation (PU & PEOU)	5	.757	Acceptable/Good
Digital Trust	3	.828	Good
Privacy Concerns	2	.825	Good
Customer Loyalty/Satisfaction	4	.824	Good

Note. Alternative classification naming convention.

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As shown in Table 6, internal consistency reliability assessed with Cronbach's alpha (α) was used to assess the quality of the measurement model. As presented in Table 6, all constructs had strong reliabilities with alpha coefficients between 0.757 and 0.828, well above the accepted .70 threshold. While high reliability cannot mathematically rule out common method bias (CMB), this set of reliability statistics helps conceptually reduce common method bias in two ways. First, the distinct reliability scores across items with varying numbers of measures per construct (between 2 and 5 items) suggest that respondents were able to differentiate between the unique underlying factors instead of giving one pervasive biased response pattern throughout the survey. Second, the strong reliability reduces the within-factor measurement error.

The internal consistency reliability was used to estimate the psychometric properties of the scales, calculated with Cronbach's alpha (α). Reliabilities of all constructs ranged from 0.757 to 0.828, exceeding the minimum recommended level of 0.70. The Pearson correlation matrix was examined to determine discriminant validity. The Pearson correlation between AI Perceived Usefulness and Customer Satisfaction was $r = 0.610$ ($p < 0.001$). This value is substantially

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below the 0.85 threshold value; therefore, the constructs demonstrate adequate discriminant validity and measure different phenomena.

Additionally, Harman's single-factor test was performed to evaluate the likelihood of Common Method Bias (CMB). All 14 items measuring the four major constructs (AI Personalisation, Digital Trust, Privacy Concerns and Customer Satisfaction) were loaded onto an unrotated EFA. The unrotated solution produced one dominant factor with an eigenvalue greater than 1, which accounted for 35.07% of the variance. As this is well below the rule-of-thumb threshold of 50%, common method variance is not considered a problem and therefore does not bias the regression analyses.

5. Discussion

5.1 Validating the TAM in the Pakistani Context

Validation of H1 provides evidence that PIA travellers perceive AI-delivered digital utilities favourably enough to incentivise them despite continuous visceral service failure manifest at the physical level. This flies in the face of the tacit assumption underlying most service recovery frameworks within the aviation industry that failure at the physical layer completely prevents positive feelings from being communicated, which is also found in [33], and that satisfaction cannot logically be attained from a digital solution where there is physical failure. Satisfaction at one utility-defined layer of the travel experience, independent of the other, speaks to digital experience's potential to decouple elements of the customer journey from the established track of failure.

One key theoretical contribution of this baseline data is that travel customers can experience attributes of the digital layer of their journey independently of their physical perceptions. Findings here suggest Pakistan International Airlines' experience is reflective of a form of service commoditisation which aligns with [29].

Overseas Pakistani travellers are not immune to the global elevation of digital service standards. Two-thirds of participants are accepting of trivial inconveniences at the physical level if it means digital interfaces function smoothly. This suggests modest digital investments provide Pakistan International Airlines with an achievable, low-risk path to turnaround compared to the expensive requirements of fleet renovation or route subsidisation it would otherwise face if attempting to outperform competitors on traditional, physical terms. From there, we provide compelling confirmation of TAM's applicability to the LMIC SOE context, pushing the literature on digitalisation and state capitalism. It is here, however, where TAM begins to fall short of explaining technology adoption by Pakistani travellers. At the moment when we validate TAM's explanatory power over the consumer's experience, TAM's assumption that trust is irrelevant to the adoption of technology becomes the key limitation of applying it to this scenario.

5.2 The Trust deficit: overcoming the confidence crisis

These structural coefficients for H2 strongly affirm the hypothesis that digital trust does not simply act as a second driver of loyalty but is instead a necessary mediating process through which AI personalisation translates to repurchase. Most importantly, this data exposes the bottleneck, with only 44% of respondents feeling comfortable allowing PIA to store their money or personal information, which creates a needlessly low baseline bar of trust for PIA to earn before being able to scale personalisation initiatives for profit, which is also indicated by [10]. Trust has been lost less through poor marketing and more evaporated through institutional stress and fear caused by PIA's financial losses and poor operations.

If we were to use the commonly cited notion of trust as being comprised of half ability or competence and half benevolence or intent, it is easy to see where the airline fell short, which is

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also indicated by [18]. Starting with ability, if passengers don't trust that the airline can run flights on time or safely deliver their luggage to its destination, they are far less likely to trust the entity with data about themselves. Turning to intent, however, the mediation analysis above already shows that digital trust is still able to directly predict loyalty, albeit by an increasingly insignificant margin when users are forced to overcome the trust gap in order to realise those benefits. Some marginal goodwill may exist out of patriotic duty that explains why the path wasn't equal to 0, but it was far from enough to eliminate the need for users to passively feel digital trust at the architectural level.

5.3 The Privacy paradox and geocultural resistance

The results of H3 have brought to light an important aspect of technology adoption processes in markets such as Pakistan, which remains underestimated by suppliers and academia originating from Western markets alike. The significant and negative value of the moderator demonstrates that the customer lifetime value accrued by personalisation can be drastically undermined if privacy concerns are elevated, which is also reflected in [5] and [6]; this implies the existence of a geocultural element to rejection. Although many base studies may treat populations as inherently accepting of large-scale surveillance capitalism practices, [45] has shown that customers from collectivist cultures with high uncertainty avoidance demonstrate pronounced negativity towards corporate surveillance, especially when institutional trustworthiness may be perceived as dubious.

Respondents of our main study also acknowledged the merits of personalisation at a fundamental level, but had several strong reservations about how much data is collected. Beyond this, there was notable concern for what happens to customers' private and financial data if they allow an organisation they do not fully trust due to lax security measures to store it, explicitly referring to unencrypted servers or unexpected data sharing with third parties. Emulating Gulf carriers' approach to personalised marketing through surveillance without understanding why these programs may cultivate feelings of revulsion over fondness will prove erroneous when customers are unsure of what is valuable versus what is invasive, which is also highlighted by [19].

5.4 Sustainability-related Insights through the Triple Bottom Line (TBL)

As demonstrated in the discussion related to the hypotheses in the previous section, the findings indicate how AI implementations affect passenger perception in the aviation industry. Charting these empirical findings on the Integrated Sustainability Model allows us to review each finding from each pillar of TBL.

5.4.1 People (Social Sustainability) - AI and Customer Satisfaction Implications

As previously stated, the "people" component of the study can be summarised by the level of technology acceptance and perceived usefulness attributed by participants—primarily our target customers. First off, the sample skews significantly towards females (59.0%) between 25–44 years of age (69.5%). These participants represent the segment of modern consumers who are working professionals and are very digitally inclined and have a refined sense of service quality; they can readily perceive the service-quality gap between airlines. As clients who consistently interact with digital technologies around the world, they expect airport and airline operators and internet service providers (who handle processes related to flying domestically and internationally) to work smoothly as well.

Support for H1 ($r=.610$, $p=.000$) highlights an important social truth; there is a strong, positive, linear relationship between AI Perceived Usefulness and CSAT. Passengers are more satisfied when they feel the airline's AI implementations—automatic flight booking, disruption

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alerts, seat selection—are useful to them during their day-to-day interactions with the airline. More importantly, this relationship shows digital usefulness to be an independent contributor to customer satisfaction, even if the airline performs its primary operational functions unsatisfactorily. In terms of human-centric design, minimising friction and improving reliability in day-to-day operations lead to happier customers.

5.4.2 Profit (Economic Sustainability) - The Loyalty-Trust-Privacy Paradox

Profit represents longitudinal revenue streams, CLV, and profitability. As shown by the results, obtaining maximum profits from your AI-relationship investments requires understanding the balance between personalisation, digital trust, and privacy. High-spender customers like business/corporate travellers (50.0%) care about digital reliability and efficiency more than any other segment. The mediation displayed in H2 is partial; Digital Trust is an expected sentiment that arises between technology acceptance and Customer Loyalty. In other words, airlines cannot overpersonalize their services and expect customers to return without a foundation of trust. The effect size decreased from $\beta=.773$ to $\beta=.485$ when trust was added to the model, demonstrating that trust is necessary to convert digital users into loyal customers. An airline must establish digital trust in order to translate AI capabilities into long-term profits.

Personalisation creates monetary value, but H3 illustrates that Privacy Concerns significantly moderate this relationship ($\beta=-.717$, $p=.033$). This creates a negative interaction effect that is the Loyalty-Trust-Privacy Paradox brought to life. Although these participants are the epitome of customers who would benefit from algorithmically suggested services, they will punish the airline by disassociating with the brand if they feel watched or harvested. Privacy concerns were not found to directly affect loyalty during either step of the analysis ($\beta=.080$, ns). When exposed to AI personalisation, privacy concerns become a weapon against the airline. If an airline does not adequately assuage the privacy concerns of its customers, they risk undermining the profitability of its AI personalisation technology by losing customers.

5.4.3 Planet (Environmental Sustainability) - The Data Tax

Although AI technologies do not directly exist in the physical world, there are real-world trade-offs for harvesting and computing immense amounts of data to feed centralised AI applications. Data centres consume massive amounts of energy, and electronic processes create physical waste. When applying AI solutions to an airline, operators must consider an optimal limit to how much they should personalise the customer experience. If an airline pushes AI algorithms too far, it may create too much overhead just running the backstage technologies needed to deliver digital convenience to passengers. For example, if enough customers take the airline up on its hyper-personalised offerings, they may see more customers using the self-check-in kiosk, opting for digital luggage receipts, and travelling with a mobile device instead of printed resources. This could realistically reduce waste produced by the airline and reduce its carbon footprint. Artificial intelligence can contribute to an airline's environmental sustainability, but only if it can find a balance so the "Planet" doesn't suffer from providing value to "People" and "Profit".

5.5 Key implications from findings

The current study adds to the original TAM framework in [35] by empirically showing how TAM fails to explain the technology adoption behaviour of customers when institutional confidence is at play within a collapsed SOE. Expanded to include TAM's perceived usefulness constructs and the four dimensions of brand trust, including a mediating factor of digital trust constructs, the current study builds on studies like [18] and [36] by showing an applicable and comprehensive model that can be used to measure technology adoption behaviour within a

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collapsing SOE context, allowing Institutional Anxiety to be operationalised as an implicit driver.

Understanding how the average PIA traveller will disregard slight physical service failures if provided with a best-in-class digital experience is a game changer. This realisation is rarely visible in traditional turnaround cases centred around airlines due to the high-cost preventative measures that are physically focused. Not only does the research provide data-backed reasoning to divert to a cheaper investment towards AI, but creating a digital service recovery framework can also help maintain valuable diaspora customer bases until physical turnaround investments can be justified financially, which is also reflected in [10]. A summary of the findings in relation to the hypotheses is given in Table 7.

Table 7

Summary of Hypothesis Testing Outcomes

Hypothesis	**Statistical Method**	**Outcome**
H1: Positive relationship between AI Perceived Usefulness and Customer Satisfaction.	Pearson Bivariate Correlation ($r = .610$, $p < .001$)	Supported
H2: Digital Trust positively mediates the relationship between AI Personalisation and Repeat Purchase Intention.	Hierarchical Multiple Regression – Two Block ($\Delta R^2 = .082$, $p < .001$)	Supported (Partial Mediation)
H3: Privacy Concerns negatively moderate the impact of AI benefits on Customer Loyalty.	Hierarchical Multiple Regression – Interaction Term ($\beta = -.717$, $p = .033$)	Supported

Note. All three hypotheses were supported by the analysis.

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As shown in Table 7, the empirical analysis comprehensively confirms that AI personalisation is a statistically significant driver of passenger satisfaction and, under conditions of adequate digital trust, of repeat purchase intention. The evidence further establishes that functional digital utility alone cannot overcome institutional trust deficits in a distressed SOE context, and that geocultural privacy concerns constitute an active moderating constraint on AI's loyalty dividend in the South Asian market.

5.6 Proposed Roadmap for Policymakers and Practitioners

Based on the key findings from this study, a proposed 10-year roadmap for policymakers and practitioners is illustrated in Figure 6.

Figure 6: Proposed Roadmap for Policymakers and Businesses

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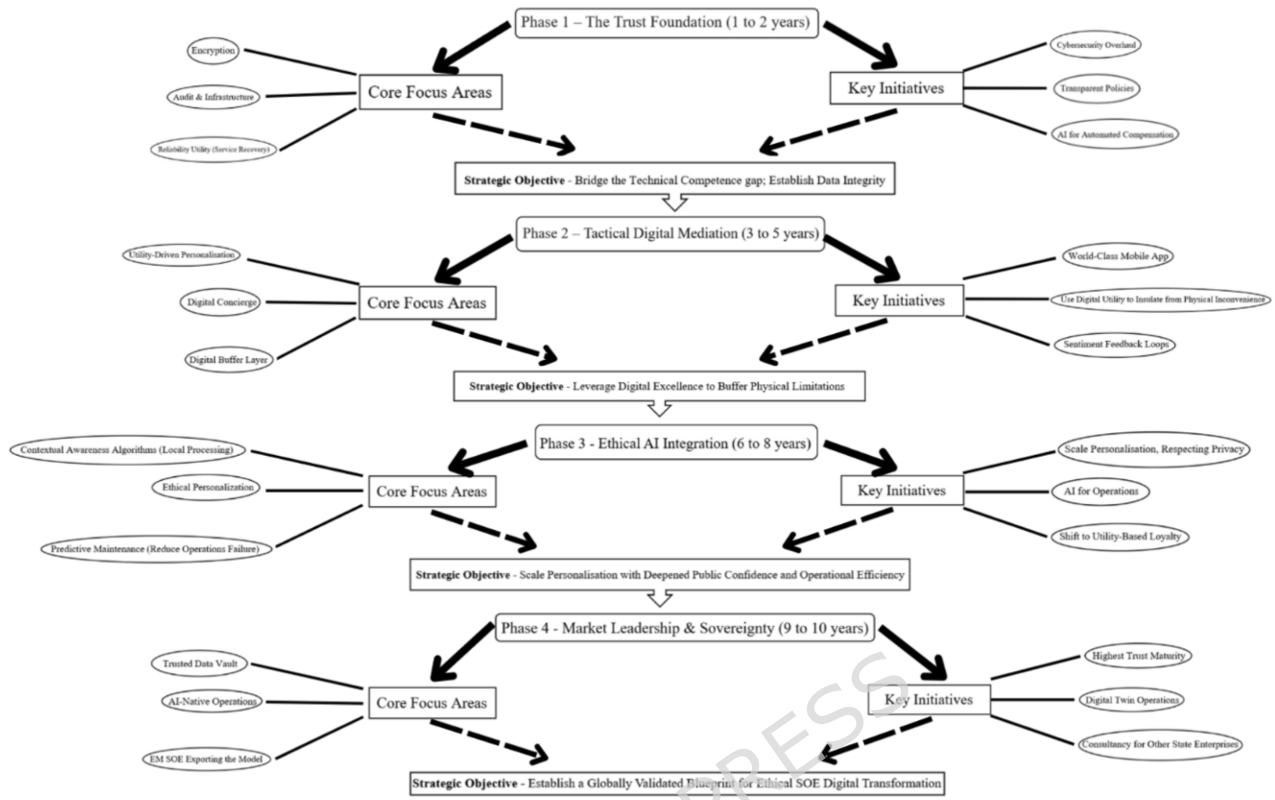

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As illustrated in Figure 6, Phase 1 sets everything in motion by laying the foundations in the firm. This means the first half of the roadmap is spent going deep on trust with a primary focus on infrastructure and data trust. Encryption, Audit/Infrastructure modernisation, and Reliability utility (how to recover from failure) are created by executing across wholesale cybersecurity modernisation, ultra-transparent policy, and AI-compensated automation. When all is said and done, the key outcome of this phase is no longer having a trust gap and gaining full data trust.

Phase 2 involves taking all that trust and starting to push back into the real world through digital servitude. Focused on digital utility-powered personalisation, launching a digital concierge and constructing a digital tactical layer. Real-world application of this plan looks like a World-Class Mobile Application and digital utility to protect consumers from the pain points of the physical world. Everything a business does now starts to get tweaked by real-time sentiment analysis feedback loops. If a business hits this phase out of the park, it has mastered digital mediation to protect its consumers from the real world.

Phase 3 involves scale personalisation while continuing to increase trust. Hyper-local (processing done on device), ethical personalisation, and predictive maintenance eliminate 90% of operational breakdowns. At this stage, businesses are scaling everything they can now that they have proven that they will not abuse consumer data. They will begin to run their day-to-day operations with AI and change the users' incentive from cash-back to utility-based value.

Phase 4 involves the end of the 10-year roadmap by proving to the world that businesses have the blueprint for how an EM SOE should go digital ethically. The organisation's 3 pillars at this point have evolved to a trusted data vault, an AI-native, and an EM SOE blueprint that businesses can sell to other countries. Market leadership is solidified by achieving the highest

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level of trust maturity, becoming a digital twin enterprise and becoming positionable as a consultancy to other SOEs.

Key success metrics (KSMs) have been charted out over the 10-year projections. Businesses' current Year 2 trust baseline will be set at >55% trusting the brand. Businesses expect that number to dip slightly due to the nature of tactical changes Year 4 will bring, setting the KSM at a >50% trust baseline. From there, businesses will grow their trust baseline to >70% by year 6 and >85% by year 10. Digital Adoption will scale up from their current year 2 adoption rates of >20% to year 4 being set at >45%, year 6 at >60% and finally exiting the decade at >80%. KSM's will mimic that of their trust baseline, starting at >55% for years 2 and 4, then scaling to >70% by year 6, finishing strong at >85% by year 10.

6. Policy, Practical and Theoretical Implications from the Study

6.1 Policy Implications

The study confirms that there are clear, pressing data governance policy imperatives for PIA, particularly when contrasting its environment with Western carriers protected by GDPR and the associated established enforcement framework. PIA cannot justify further inaction on the grounds of simply awaiting a regulatory mandate. It must take proactive steps in developing a corporate data governance structure that adheres to international best practices – such as transparent notification of data collection, precise definitions of data retention duration, and unequivocal bans on unauthorised third-party data sharing – for both business reasons and ethical obligations before further advanced AI personalisation efforts are implemented. Additionally, for sustainability practices that may improve customer loyalty, there is scope for airlines like PIA to align their corporate social responsibilities with the sustainable development goals (SDGs) for SDG 9, SDG 11 and SDG 12 which may ensure an improved organisational focus on innovation (like AI diffusion), infrastructure, communities (e.g., customers' collective consensus of a business' reputation) and responsible consumption (e.g., what is the business doing to represent itself as being a more sustainable business?).

6.2 Practical Implications

The findings that 68% of passengers will forgive physical operational inadequacies based on a superior digital experience entirely shift PIA's priorities toward digital, rather than a capital-intensive physical restructuring it cannot afford. Management must allocate the limited available resources toward developing a user-centred and secure digital architecture that embraces AI, in particular to enhance its ability to provide proactive, AI-driven notifications and compensations for delays, automate end-to-end service recovery and rebooking without the need for human intervention at counters, and provide clear opt-in controls regarding data usage for personalisation. These three steps are practically feasible, relatively cheap to implement compared to significant infrastructure upgrades, and validated as drivers of customer loyalty in the PIA context.

6.3 Theoretical Contributions

By testing and establishing the validity of the hybrid TAM-Brand Trust-TBL (TAMBTTBL) theory within an SOE and emerging-market setting, this study offers a well-founded and evidence-based framework for future academic inquiry into technology adoption amid institutional vulnerability, geocultural nuance and sustainability. The operationalisation of Institutional Anxiety as a context-bound de-escalator of TAM validity and empirical verification of Privacy Concerns as a culturally-bound moderating effect on AI's loyalty benefit add precision to technology adoption models applied to high-stakes scenarios. As digital transformation initiatives penetrate all sectors of SOEs in the Global South, institutional anxiety, privacy and

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sustainability concerns should be seen as essential, not optional, components of the standard theoretical framework on AI in SOEs.

7. Limitations

The cross-sectional time horizon allows the snapshotting of attitudinal data at one point, making any temporal analysis of causal relations impossible. Customer loyalty is an evolving concept that changes with experience. Longitudinal tracking of passenger responses at each stage of the AI implementation phases would lead to stronger causal inferences on the directional and persistent nature of the relations and further inform our understanding of how passenger trust is built and eroded by digital interventions.

Relying on survey data alone, while suitable for hypothesis testing, limits the richness of our insights into customer psychology and that of a qualitatively rich investigation. A fundamentally cognitive and affective construct like the Privacy Paradox would benefit greatly from exploratory research where semi-structured interviews could probe the underlying psychological mechanisms through which customers feel both a need for personalisation and a deep discomfort with being observed by the very systems that offer it.

In spite of purposeful sampling according to travel purpose, a sampling bias was inherent in the use of online surveys; this method targets internet-active, digitally literate respondents and systematically excludes less digitally engaged and older passengers. These customers are likely to have a different AI perception profile and a different understanding and level of perceived threat from surveillance than the more digitally fluent segment. Airport-based paper surveys could complement online methods for capturing less-digitised segments.

8. Potential Areas for Future Studies

Given the finding of the Private Paradox among customers, PIA should not directly roll out sophisticated AI-powered personalisation, which, given the required data collection, directly activates fear and brand avoidance. A phased deployment architecture is advised: start with less-intrusive but highly functional AI applications such as multilingual chatbots that deliver speedy answers to customer queries, dynamic luggage tracking devices, and an effortless digital check-in. These applications demonstrate digital capacity, build fundamental digital competence on which customers can eventually feel they can rely, and allow for incremental trust to be built. This trust, in turn, allows passengers to voluntarily opt in to more invasive applications such as sophisticated AI-based personalisation of services, in phases, as trust gradually increases with exposure to reliable low-risk digital solutions.

To tackle the demonstrated trust deficit (only 44% of customers were willing to share personal data with PIA), and as the geocultural dimensions of the Private Paradox reveal, customers need direct control over what data PIA uses, why it is used and how long it will be kept. PIA should make this explicit with a passenger-accessible data dashboard, a new feature that could be built directly into the existing PIA application, that shows customers exactly which categories of their personal data are held by PIA and the precise reasons why they are used, while offering detailed options for customers to manage the extent of data sharing. This directly addresses customers' perceived lack of transparency and institutional mistrust.

Since, according to the evidence presented in the study, 68% of customers were willing to waive small delays in exchange for digital services, PIA's AI deployment strategy should also pivot from solely basic operational functionality towards anticipatory digital customer recovery processes. Operational AI should monitor flight conditions constantly, identifying potential disruptions in real time. If a flight's delay probability reaches a predefined threshold, a fully automated, highly personalised message should be dispatched via PIA's mobile app to each

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impacted customer. This notification should detail the flight status transparently, explain the cause of the delay and offer real-time automated alternative travel arrangements and compensation options, bypassing the physical counter. This digital-empathy interaction, which is capable of managing crises directly rather than after they occur, effectively defuses the reputational damage previously inflicted by operational failures and systematically builds trust at an organisational level and thus contributes to the rebuilding of PIA's reputation in the eyes of its diasporic passengers.

9. Conclusions

To assess whether sustainability-inspired, AI-powered digital personalisation can measurably improve customer loyalty for Pakistan International Airlines (PIA), it was first shown that digital convenience is indeed a significant direct predictor of customer satisfaction ($r = 0.610$, $p < 0.001$). In other words, digital value can help to abstract away the passenger experience from poor on-ground operations and provide a low-risk recovery vector for the airline. Second, it was necessary to expand upon the TAM to include two significant psychological limits to digital personalisation; (1) digital trust is an essential prerequisite partial mediator for cultivating customer loyalty into long-term economic viability ($\beta = 0.406$, $p < 0.001$) and (2) the "Privacy Paradox" held true that privacy concerns strongly and significantly moderate the link between AI personalisation and customer loyalty ($\beta = -0.717$, $p = 0.033$). In other words, if passengers feel as though they are being digitally manipulated by predatory data collection, then they will withdraw from the company altogether—nullifying the economic benefit of your algorithms. Finally, to help PIA best optimise their AI deployments towards the Triple Bottom Line, they must balance the People and Profits of human-centred digital convenience and secure data transparency to achieve customer lifetime value, without forgetting about the "cost" of data tax and electronic waste needed to fuel genuine paperless sustainability efforts (Planet).

RO1 was achieved by expanding upon the classic Technology Acceptance Model by adding non-traditional TAM factors that reflect original psychological and sustainability motivations of users within a Lower-Middle-Income Country State-Owned Enterprise context. Benchmark indicators validated the traditional notion that PU significantly predicts CSAT. However, to increase the model's novelty, AUT was hypothetically dropped due to literature illustrating trust's indispensability to technology adoption. Fulfilling the research paper's requirements for two substantial original extensions, this paper: (1) demonstrates DT to be a significant partial mediator between AI and CL, thereby concluding technological usefulness does not guarantee loyalty if perceived operationality is not trusted; (2) retains and successfully measures the privacy paradox (PP) as a sharp negative moderator of AI and CL. One original contribution of this study is that it empirically demonstrates travel consumers can divorce their digital experience from the physical aspects of their journey. In times of acute organisational distress, digital usefulness can independently satisfy customers.

RO2 was achieved by designing and deploying a valid empirical study that reflects PIA's geocultural and organisational context. Targeting customers who both care about and have a significant influence over airlines' operational success, the survey captures high-frequency corporate and business travellers who value digital convenience as well as leisurely and religious travellers who make up a majority of PIA's diaspora and umrah audiences. Drawing from Pakistan's large working-age population, the majority of respondents were between 25 and 44 years old and could properly distinguish between PIA and competing Gulf airlines. An unexpected finding from the study was the negative attitude towards data monetisation, which

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was not present in Global North surveys. As Pakistan is a collectivist society with high uncertainty avoidance, trust plays an important role in the acceptance of new technology. Only 44% agreed that the airline could store their personal and payment information due to security concerns. This will translate to customers being wary of AI-driven hyperpersonalization if done to the level of Gulf competitors.

The results were then applied to the Integrated Sustainability Model to illustrate how each Sub-Goal can be addressed within the TBL. Under social sustainability, automation was shown to significantly reduce friction and improve CSAT. Under economic sustainability, it was shown that corporate profits from AI can only be optimised when users do not boycott the brand due to excessive personalised advertising. Under environmental sustainability, this paper found that although data storage requires the use of large data centres that require energy to cool, hyperpersonalization can help users transition to sustainable practices.

Author Contributions: Muhammad Bilal wrote the literature review and results sections, along with collecting and analysing the data. Wajahat Usman wrote the abstract and introduction sections, along with testing the research instrument. Sayed Abdul Majid Gilani worked on sections within the literature review and discussion sections. Kiran Tangri and Raymond Lihe worked on parts of the literature review, results and implications sections. Firas Armosh and Ansarullah Tantry worked on parts of the discussion, limitations, recommendations and conclusion sections as well as carrying out editing and proofreading.

Declarations

Ethical Approval/Declaration: The ethics for the study were approved by the University Research Ethics Committee (UREC) at Ulster University in accordance with the Ulster University Code of Practice for Professional Integrity in the Conduct of Research. The Ethics Code is UUREC 2026/02/16. The research was carried out following the guidelines of the University Research Ethics Committee (UREC) at Ulster University. Finally, the research involving the participants complied with the Declaration of Helsinki.

Field permission: Informed oral consent was obtained from all individual participants included in the study, including local authorities. Each participant was fully informed about the purpose, procedures, and potential impacts of the research, and their participation was voluntary.

Consent to Participate: All participants gave written consent to participate in the study. It should be noted that the study did not involve participants under the age of 18.

Consent to Publish: Not Applicable.

Data Availability Statement: The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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