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How AI-Driven Chatbot Agility Capability Drives Customer Loyalty in Airlines: A Dual-Mediating Path of Perceived Usefulness and Customer Satisfaction

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Abstract

As airlines increasingly deploy an AI-Driven Chatbot (ADC) to enhance service efficiency, this study aims to investigate how the agility capability of ADC drives perceived usefulness and satisfaction, ultimately enhancing customer loyalty in a competitive aviation industry. Drawing on a survey of 303 respondents in South Korea, Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were employed for empirical analysis. The structural model examines how the agility capability of airline ADC—modeled as a second-order construct comprising competence, responsiveness, speed, and flexibility—shapes the consumer experience. The findings reveal that agility capability positively influences perceived usefulness, which in turn enhances satisfaction and ultimately fosters customer loyalty. Notably, neither agility capability nor perceived usefulness exerts a direct effect on loyalty; their influence is fully channeled through satisfaction, highlighting satisfaction as the pivotal mechanism that transforms agility capability into customer loyalty. These results offer meaningful insights into customer behavior, contributing to the strategic utilization of ADC for better customer experience.

Keywords: AI-driven chatbot; airline; agility capability; satisfaction; customer loyalty; customer experience

1. Introduction

In a 2025 survey conducted by Salesforce of 6500 service professionals across 40 countries, nearly two-thirds (63%) of customer service organizations have implemented Artificial Intelligence (AI) in at least one service channel. Within the travel and hospitality industry specifically, AI integration has achieved a 15% reduction in service costs alongside a 19% increase in customer satisfaction [1]. These findings underscore that firms are relying on AI-driven chatbot (ADC) systems gradually by increasingly deploying them to optimize cost efficiency and to ensure round-the-clock customer support [2].

As these automated technologies become pervasive, researchers have increasingly emphasized the importance of examining chatbots not merely as functional tools, but as interactive communication interfaces that mediate Human–Computer Interaction (HCI) between corporations and consumers [3,4]. In this capacity, chatbots facilitate service communication by simulating human-like engagement. ADCs, which are defined as computer programs designed to converse with human customers over the internet [5], maintain consistent and automated support by replicating anthropomorphic interactions.

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Leveraging Natural Language Processing (NLP), these systems interpret and respond to human language through text- or voice-based modalities [6]. Moreover, the strategic significance of ADCs lies in their capability to resolve a contemporary paradox in service operations beyond their automation: to maintain global scale while delivering personalized service. This tension defines the core challenge of agility capability through four essential pillars: competence, flexibility, speed, and responsiveness [7–9]. By integrating these capabilities, ADCs can serve as the digital engine that allows an organization to resolve this tension—scaling operations without compromising precision [10].

In rapidly changing service environments, organizational agility is increasingly associated with the ability to efficiently process information, adapt to customer needs in real time, and maintain consistent service quality through digital technologies [11]. An ADC contributes to agility capability by automating repetitive interactions, accelerating response time, and supporting continuous customer engagement across multiple service channels [12]. Furthermore, chatbots' conversational and data-processing capacities enable organizations to respond flexibly to variable customer demands while sustaining operational efficiency and service consistency [13].

The implementation of interactive ADCs is on the rise in a variety of industries, particularly in the hospitality and airline sectors, to facilitate customer inquiries, booking processes, and service management. Several studies have demonstrated that these ADC interactions exert a substantial influence on customers' booking intentions and engagement with tourism and hospitality services [14–16]. The effective interaction between ADC and customers can help narrow the "intention-behavior gap" by providing real-time assistance and personalized recommendations. This interaction has also reduced hesitation during the decision-making process [17].

Empirical evidence further indicates that high-performing airline chatbots can improve customer satisfaction by 15 points during irregular operations while resolving issues 35% faster than traditional call centers [18].

Moreover, within the hospitality industry, customers increasingly expect personalized treatment and emotionally responsive communication. In this context, ADCs function as a pivotal service touchpoint that shapes customers' perceptions of professionalism, trust, and overall service quality [19]. By delivering immediate and tailored interactions, ADC technologies can strengthen customer trust and enhance the overall service experience in the airline industry. AirAsia, KLM Royal Dutch Airlines, and Lufthansa, for instance, have adopted ADC systems to deliver fast, consistent support across the messaging apps and mobile channels their passengers already use. AirAsia's strategic emphasis has been on minimizing customer wait times and managing large volumes of inquiries in 11 languages, leading to notable enhancements in both response speed and customer satisfaction [20].

Concurrently, KLM stressed conversational and personalized interactions with its ADC, thereby enabling customers to search, book, and manage flights using familiar applications such as Messenger and voice assistants, specifically through the implementation of the Blue Bot service [21]. In contrast, Lufthansa focused on real-time disruption management by assisting customers in handling delays, cancellations, and missed connections more efficiently during stressful travel situations [22]. A close examination of these three cases reveals several common factors among them. These factors include the ability to provide instant responses, the capability for seamless integration with airline systems, 24/7 accessibility, and the ability to resolve problems without requiring prolonged waits that come with human agents. These examples demonstrate how ADCs can enhance operational efficiency while enhancing customer service quality. Overall, the adoption of ADCs highlights the growing importance of AI-driven communication tools in creating faster, more responsive, flexible, and customer-centered airline services.

Given the emergence and functions of ADCs in the airline industry, several research questions are identified:

- How does an ADC in the airline industry affect customer experience outcomes such as customer loyalty?
- Does the agility capability of ADCs in airlines influence customer loyalty through perceived usefulness and satisfaction?
- How do airlines using ADCs develop them for the future as part of their business strategies?

Addressing these questions responds to three gaps in the current literature. First, prior research has predominantly treated the individual attributes of conversational agents—such as responsiveness or speed—as isolated predictors, without considering whether they form an integrated agility capability; in the absence of a higher-order conceptualization, the literature risks attributing to separate attributes what in fact reflects a common underlying capability. Second, although technological attributes are widely assumed to enhance customer loyalty, it remains underspecified whether this effect operates directly or is transmitted through customers' cognitive and affective evaluations. Third, agility has been theorized primarily at the organizational level, and its manifestation in consumer-facing service technologies such as ADCs remains scarce.

The originality of this study lies in the fact that prior research has neither examined the utility of ADCs as mediated by perceived usefulness and satisfaction, in relation to customer loyalty, nor explored them based on the agility capability of ADCs in the airline industry.

It aims to investigate how the agility capability of ADCs impacts customer loyalty by examining the mediating effects of perceived usefulness and customer satisfaction in the airline industry through a quantitative structural equation model. Thereafter, this research explores how ADCs in airlines impact customer experience. The study consists of five main sections. First, the literature review explores the factors constituting agility capability and their significance in relation to perceived usefulness, customer satisfaction, and customer loyalty. Secondly, it presents the relationships among the variables and the hypotheses. Third, the methodology is described, including the survey design, Confirmatory Factor Analysis (CFA) for data analysis and Structural Equation Modeling (SEM) with emphasis on hypothesis outcomes. Lastly, this study thoroughly discusses the research findings and their academic and managerial implications.

2. Literature Review

2.1. Agility Capability of ADCs

Agility capability refers to a firm's capacity to meet customer needs and capitalize on technological developments as opportunities. According to the literature on the subject, agility is widely conceptualized and not considered a single attribute, but rather a multidimensional, higher-order capability emerging from the interplay of several complementary sub-dimensions [7–9]. ADC is a strategic resource that helps secure a competitive position, thereby strengthening a firm's market standing [7]. In the hospitality industry, agility capability enables rapid digital services, such as mobile check-in and personalized communication, which have been regarded as successful innovations [23]. In the hotel sector, a key segment of the hospitality industry, IT resources enable hotels to transform traditional service models into digitized customer touchpoints by sensing and responding to shifting market demands. This strategic operation of IT resources, including ADCs, functions as a vital shield, helping hospitality companies stay flexible and competitive even during market instability or unexpected emergencies [23]. Similarly, in the banking sector, chatbots respond promptly to customer inquiries, facilitate the resolution of customer issues, and support the execution of routine banking transactions [9].

In line with this multidimensional perspective, prior studies conceptualize agility capability as a higher-order construct, manifested through four interrelated first-order dimensions: competence, flexibility, responsiveness, and speed [7–9].

Competence denotes the inherent capacity and readiness of an ADC to operate effectively [24,25]. This encompasses several key aspects, including the ability to interpret customer inquiries and generate precise, relevant answers [26]. It also involves balancing operational efficiency with customer experience and environmental sustainability [27–29], strengthening the cognitive connection between customer and technology [30], and encouraging customers to treat the agent as a reliable partner rather than a static tool [31,32]. Flexibility represents the system's aptitude for adjusting to changing customer demands [33] while lowering the customer's cognitive burden through customization [34]. Responsiveness is described as the capacity to offer accessible and instantaneous assistance [35], mirroring human-like conversational flows through the rapid and accurate exchange of data [36] and strengthening perceived usefulness through real-time interaction [37]. Speed captures the temporal efficiency with which the system retrieves data and streamlines the customer's decision-making process [38], signaling technological sophistication and fostering customer trust [39]. Although each dimension captures a distinct facet, they are theoretically expected to co-occur and reinforce one another, as they jointly reflect the same underlying capacity to sense and respond to customer demands; their conceptual interdependencies are examined in Section 3.1.

It is important to note that these four dimensions do not operate in isolation; rather, they represent complementary manifestations of a single underlying agility capability. Agility capability comprises fundamental properties crucial for organizational survival and competitive advantage [40]. Ultimately, the agility capability of an ADC contributes to long-term customer loyalty. However, this study suggests that the impact occurs indirectly, shaping customers' perceptual and evaluative responses instead of acting in a direct manner.

2.2. TAM, ECT, and Intention Behavior Gap

Prior studies have drawn on the Technology Acceptance Model (TAM) to identify the factors influencing customer adoption. This model suggests that external technological features do not directly determine outcomes, but shape customer perceptions—Perceived Usefulness (PU) and Perceived Ease of use (PEOU). These two perceptions positively impact customer attitudes, usage, and behaviors [41]. Recently, this model has been developed to show how PU and PEOU significantly influence customer satisfaction. Customer satisfaction is not affected by technology itself, but by how customers perceive technology [42]. In the context of information technology, the consideration of technological solutions, such as ADCs, as both practical and capable of delivering tangible advantages has been demonstrated to result in a marked shift in customer attitudes, leading to an enhancement in satisfaction levels [43]. Although TAM specifies both perceptions, the present study focuses on perceived usefulness. Post-adoption research indicates that the effect of ease of use diminishes once customers become familiar with a system, whereas usefulness remains the dominant determinant of satisfaction [44]. In information systems (IS) research, Expectation-Confirmation Theory (ECT) also addresses post-adoption behavior and explains the relationship between perceived usefulness and satisfaction [44]. Customer satisfaction is determined by comparing prior expectations before usage to actual perceived performance after usage [45]. Satisfaction with technology is a critical factor in determining the customer's propensity to continue utilizing it consistently. Satisfaction arises from the confirmation of initial expectations and the continued perception of usefulness [44]. The concept of perceived usefulness has been identified as a critical cognitive belief that has the capacity to directly reinforce a customer's favorable feelings toward technology, such as an ADC. When technology provides valuable information or practical solutions, it validates the customer's decision, resulting in customer satisfaction [44]. By extending ECT to mobile internet services, an environment like ADC usage, online services must be perceived as useful to sustain customer satisfaction [46]. Although TAM predicts the intention to use ADCs effectively, a substantial intention–behavior gap persists in industries such as airlines, hotels, and other hospitality sectors [17]. This discrepancy indicates that cognitive acceptance of ADC usage does not always convert into actual usage behavior. In this context, satisfaction plays a critical mediating role in bridging this gap. This phenomenon is theorized to facilitate the development of consistent loyalty and transactional behavior, as indicated by numerous studies [47,48]. Satisfaction, in turn, fosters customer loyalty, as established in the satisfaction-loyalty theory [49].

2.3. Satisfaction-Loyalty Theory

According to satisfaction-loyalty theory, it acts as an antecedent of satisfaction, which, in turn, builds up customer loyalty. When a customer perceives a service as helpful, perceived usefulness increases, which subsequently strengthens customer satisfaction. If the customers consistently experience this utility, their cognitive evaluations evolve into a state of satisfaction. Consequently, they become less vulnerable to the allure of competing alternatives. Higher levels of satisfaction further contribute to customer loyalty [50]. When customers perceive IT technology as useful, it fulfills their utilitarian needs and strengthens their psychological commitment to the brand or service, thereby fostering customer loyalty [44]. The relationship between perceived usefulness and satisfaction serves as the rational foundation for long-term loyalty. A recent study of AI in e-commerce shows that perceived usefulness is a central cognitive state shaping customers' intention to remain loyal to an AI platform [51]. Similarly, another study of mobile application usage has found that perceived usefulness has a significant positive effect on customer satisfaction, which subsequently contributes to customer loyalty [52].

3. Hypotheses

The research model of the following inquiry consists of the following elements: agility capability, perceived usefulness, satisfaction, and customer loyalty. In the following paragraphs, each of these elements is described in detail in the context of airline ADCs.

3.1. Agility as a Second-Order Capability

Agility has been conceptualized as a multidimensional capability since the seminal work [40]. which identified four fundamental agility capabilities: its capacity to interpret inquiries accurately (competence), adapt to varied customer demands (flexibility), respond without delay (responsiveness), and process tasks efficiently (speed). This four-dimensional structure has become the dominant framework in agility literature and has been consistently adopted in subsequent conceptual and empirical work [40,53,54].

3.1.1. Competence

The research identifies a broad set of sub-capabilities under this heading, including appropriate technology, service quality, cost-effectiveness, operational efficiency, and knowledgeable and empowered personnel [40]. In the ADC context, competence captures the system's proficiency in accurately interpreting airline-related inquiries and generating precise, relevant responses. This proficiency is supported by knowledge derived from extensive training data, which enables the system to provide customer support across different service stages [26,39,55]. It reflects customers' expectations of ADC's intelligence, expertise, and effectiveness in comprehending airline service needs [56,57]. Consequently, a highly competent ADC is regarded as a functional asset that directly relieves passengers' concerns and resolves their inquiries [12,58]. Competence, therefore, serves as the foundation of ADC agility, providing the essential capacity on which the other capabilities depend.

3.1.2. Flexibility

Flexibility is defined as the ability to perform various work and accomplish different objectives while utilizing the same resources [40]. It entails the capacity to recalibrate existing resources in response to fluctuating demands, rather than to expand those resources. A flexible automated system, such as an ADC, has the capacity to address a variety of issues, recover from errors without disrupting the interaction, and adapt to customer intentions [51]. In the context of ADC, flexibility signifies the system's capacity to adapt to evolving customer demands [33], thereby circumventing rigid, standardized responses and maintaining a personalized, customer-centric experience [33,34]. Flexibility is itself contingent: an ADC possesses the ability to adjust exclusively to those demands that it has recognized. The exercise of flexibility presupposes that the system has first detected an exigency for adaptation, a process that is facilitated by responsiveness.

3.1.3. Responsiveness

Responsiveness is the ability to identify changes and respond to them, reactively or proactively, and to recover from them [40]. It encompasses both the sensing of environmental change and the initiation of an appropriate response. Within the ADC framework, responsiveness is described as the system's capacity to provide accessible and instantaneous assistance [35] and to mirror human-like conversational flows through rapid, accurate data sharing [36], converting a standard transaction into a dynamic interaction [37]. Responsiveness is thus linked to competence and flexibility. It is the mechanism through which the system's underlying capacity is mobilized in the direction that the situation demands. From a service-quality perspective, responsiveness is regarded as a hallmark of system reliability. Customers frequently equate immediate interaction with overall system competence [59], and a highly responsive interface reduces non-value-adding delay, signaling that the system is equipped to minimize customer uncertainty [60]. Nevertheless, the value of a response depends fundamentally on its promptness, which is determined by the concept of speed.

3.1.4. Speed

Speed—termed "quickness" in the original framework—is defined as the ability to carry out tasks and operations in the shortest possible time [40]. It is the temporal dimension of agility. From the perspective of ADC, speed is indicative of the efficiency with which the system executes a task [32]. This efficiency is characterized by the rapid retrieval of information and the streamlining of the customer's decision-making process [38]. The enhanced processing and response speeds of such systems reduce the cognitive and temporal costs experienced by customers, and real-time responsiveness has been identified as a core baseline requirement for automated service systems [61,62]. Yet speed is not an independent virtue. A rapid but inaccurate response reflects a failure of competence; a rapid but misidentified response reflects a failure of responsiveness. Conversely, an accurate and well-adapted response delivered too late is of no value in a time-critical airline context, such as a missed connection. Therefore, the concept of speed is derived entirely from its conjunction with the other three capabilities.

3.1.5. The Case for a Second-Order Specification

The four capabilities are interdependent, constituting a system rather than a set of separable attributes. Each capability is a necessary but insufficient condition for agility. Treating them as independent predictors would imply that a firm could increase one while holding the others constant. However, this assumption is inconsistent with the conceptualization of the construct. Following the recommendation to model capabilities at the level at which they are theorized [63], the present study specifies agility capability as a second-order reflective construct manifested by four first-order reflective dimensions. The four dimensions are thus treated as alternative manifestations of a common underlying capability rather than as its constituent causes. All subsequent hypotheses are formulated at the level of the higher-order construct.

3.2. Agility Capability and Perceived Usefulness

The relationship between agility capability and perceived usefulness is a well-documented phenomenon in the field of chatbot research. In the context of customer service, the concept of perceived usefulness emerges as a particularly salient factor, given customers' expectations for prompt and accurate responses to their inquiries [64]. Prior studies have accordingly incorporated responsiveness alongside usefulness and ease of use in models of chatbot adoption. These studies have demonstrated that a chatbot's ability to respond efficiently and quickly shapes customers' evaluations of its utility [65], and chatbot usability and responsiveness have been shown to enhance the online customer experience [38]. This reasoning is consistent with the IS Success framework, in which technical system-quality attributes—such as operational speed and execution efficiency—function as antecedents that shape customers' cognitive assessment of a system's ultimate utility [66].

Crucially, these dimensions are theorized as complementary manifestations of a single underlying capability rather than as independent reflective components [40]. The present study proposes that the overall agility capability of an ADC positively shapes customers' perceived usefulness as a second-order construct reflected by these four first-order dimensions. Therefore, the following hypothesis is suggested:

H1. *The agility capability of ADCs positively influences perceived usefulness.*

3.3. Agility Capability and Satisfaction

Beyond its instrumental value, agility capability shapes customers' evaluative response to the service encounter itself. The extant literature on service quality has long established that responsiveness—defined as the degree to which service providers are inclined to assist customers and provide prompt service—constitutes a core determinant of customers' satisfaction with a service encounter [59]. Prior studies indicate that responsive ADCs eliminate the waiting times traditionally associated with human agents. This, in turn, has been demonstrated to meet customers' expectations for constant availability [35]. The use of flexible systems sustains a personalized and customer-focused experience [33]. Evidence from the banking sector further demonstrates that chatbots exhibiting these capabilities enhance service quality and strengthen customer relationships [9]. Moreover, the technical swiftness of a platform fosters customer confidence and trust [39]. Considered as a whole, these arguments suggest that ADC's agility capability generates a favorable evaluation of the service experience, irrespective of the functional outcome achieved. This effect is particularly salient in airline contexts, where customers frequently face time-sensitive and stressful situations such as delays and cancellations. As a result, the following hypothesis is put forward:

H2. *The agility capability of ADCs positively influences satisfaction.*

3.4. Perceived Usefulness and Satisfaction

Satisfaction mediates the relationship between the effect of perceived usefulness and customer behavior in extensions of TAM [67]. Multiple empirical studies consistently show that perceived usefulness is a highly effective predictor of customer satisfaction across a wide array of online platforms, mobile applications, and digital environments [44,68,69]. Specifically, they highlight that when a system provides high utility, it directly correlates with increased customer satisfaction. The more useful interactive digital platforms are, the more satisfied customers become [70]. Another study also explains that when customers recognize ADC's high utility and performance benefits, they are more likely to be satisfied [71]. The perceived usefulness is not just positively associated with customer satisfaction, but it functions as a key driver of customer satisfaction in ADC, one of the artifacts of IS [42]. Another finding concerning customer behavior in e-commerce identifies perceived usefulness as a significant antecedent of customer satisfaction [67]. Considering this, the following hypothesis is developed.

H3. *Perceived usefulness positively influences satisfaction.*

3.5. Satisfaction and Customer Loyalty

In the context of ADCs in IS, customer satisfaction determines whether customers remain loyal to the company deploying the ADC [72,73]. This fact indicates that customer satisfaction plays a critical role in fostering long-term customer engagement with cutting-edge technology [74]. The customer keeps using ADC and recommends its services to others [13,48]. Higher satisfaction with ADC interactions leads to stronger customer loyalty, reflected in customers' intention to continue using the chatbot and to engage in positive word-of-mouth. A prior study has confirmed a strong, positive, and statistically significant correlation between customer satisfaction and loyalty. It argues that satisfaction is the most consistent predictor of a customer's psychological commitment to the corporate brand formation [75]. Another study of ADCs in the hospitality industry reveals that customer satisfaction exerts a substantial and immediate influence on loyalty. Satisfaction acts as the central engine for customer commitment and customer loyalty [76]. Hence, the following hypothesis is advanced:

H4. *Customer satisfaction positively drives customer loyalty.*

3.6. The Mediating Roles of Perceived Usefulness and Satisfaction

In addition to the individual relationships posited above, the model proposes a sequential mechanism through which agility capability is converted into loyalty. This reasoning aligns with the cognition–affect–behavior framework, which posits that cognitive appraisals precede affective responses, which in turn drive behavioral intentions [77,78]. The present study also aligns with TAM's core premise that system characteristics influence behavioral outcomes indirectly, through perceptual mediators [41]. In accordance with this logic, previous studies have shown that perceived usefulness exerts an indirect influence on loyalty through customer satisfaction [79]. We expect the effect of agility capability on customer loyalty to be transmitted through perceived usefulness and satisfaction rather than exerted directly. Therefore, the following hypotheses are suggested:

H5. *Perceived usefulness and satisfaction mediate the relationship between agility capability and customer loyalty.*

H6. *Satisfaction mediates the relationship between perceived usefulness and customer loyalty.*

4. Materials and Methods

4.1. Research Design and Sample Selection

This study employs CFA followed by structural equation modeling SEM to test the research model. The questionnaire was distributed from April 2026 to May 2026. This study employed a convenience sampling approach, characterized by a non-probabilistic and self-selected participation design, in accordance with Tarhini et al.'s recommendations [80]. The survey link was distributed to the public through social media platforms. To ensure that respondents could meaningfully evaluate the focal constructs, the survey was administered only to those who had prior experience using an airline's ADCs. Respondents without such experience were not given the opportunity to complete the questionnaire. Respondents' experience with ADCs in other industries was separately recorded as part of the demographic questions. This recruitment approach optimizes data-collection efficiency but introduces limitations regarding the external validity and generalizability of the findings. These limitations are acknowledged in Section 6.3. A total of 303 valid responses, all from airline ADC customers, were retained for the final analysis; no cases were excluded for incomplete or invalid responses, as the survey required a response to every item before submission.

The required sample size was determined based on established guidelines for structural equation modeling. First, Hair et al. recommend a minimum ratio of 10 respondents per observed variable; with 23 observed variables in the present model, this criterion requires at least 230 respondents [81]. Second, a further study by Bentler and Chou suggests a minimum of five respondents per estimated parameter; with 56 free parameters, this criterion requires at least 280 respondents [82]. Third, another study recommends a minimum of 200 cases for maximum likelihood estimation to ensure the stability of parameter estimates. The final sample of 303 respondents satisfies all three criteria (ratios of 13.2:1 and 5.4:1, respectively) [83]. In addition, Hoelter's critical N for the final model was determined to be 154 at the 0.05 level and 164 at the 0.01 level. These values are both substantially below the achieved sample size, confirming that the sample was sufficiently large for the study's purposes.

4.2. Survey Design

To execute the quantitative methodology, a 23-item survey was developed based on the research model illustrated in Figure 1. These items were adapted from a variety of industry research on artificial intelligence, as detailed in Table 1, and all items utilized a 5-point Likert scale. To establish content validity, the initial item pool was reviewed by two professors of business administration. Their feedback was used to refine item wording and to confirm that each item aligned with its intended construct. The survey was subsequently translated into Korean with the assistance of two experienced translators to guarantee clarity for the participants. To maintain strict cultural and linguistic equivalence across the scales, the translation process adhered meticulously to the methodological guidelines delineated by Ruvio and Shoham [84]. The refined instrument was subsequently subjected to pilot testing with 10 respondents over five rounds. Based on their feedback, the items were adjusted to ensure consistent terminology for the ADC across the questionnaire and to confirm that all items were appropriately tailored to the airline industry context.

4.3. Common Method Bias

Because the data were collected from a single source, common method bias (CMB) was addressed procedurally and statistically. The study's design was meticulously crafted to ensure procedural voluntarism and anonymity. Respondents were assured there were no right or wrong answers, and items were presented in randomized order [85].

Statistically, employing Harman's single-factor test showed a predominant factor accounting for 62.55% of the observed variance. Although this value exceeds the 50% threshold, the test is widely regarded as insensitive [85]. The elevated inter-construct correlations reflect the theoretically expected proximity of the constructs, particularly satisfaction and loyalty, rather than method variance, as shown in the discriminant validity analyses (see Section 5.3). Nevertheless, because the single-factor result exceeds the conventional threshold, the possibility of common method bias cannot be entirely ruled out, and this is acknowledged as a limitation of the study. Future research employing multi-source or temporally separated data collection would help further mitigate this concern.

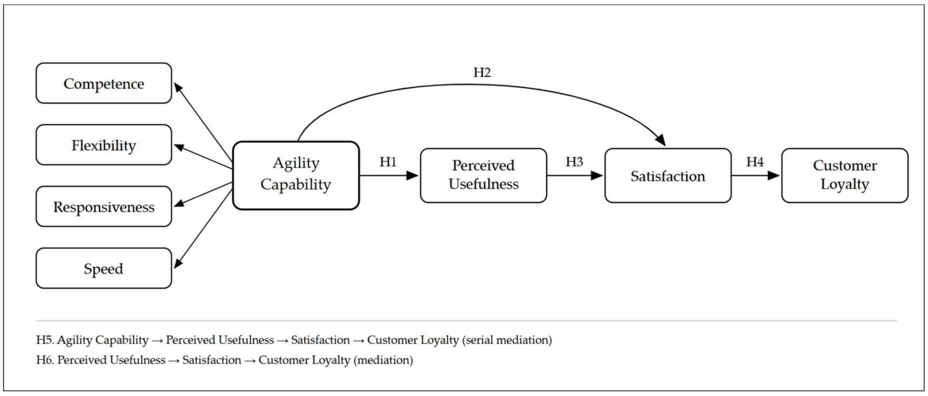

Figure 1. Research Model.

4.4. Use of Generative AI

During the preparation of this work, the authors used Gemini 3.5 Flash and Claude Opus 4.8 for language editing and to cross-check their own interpretations of the results. All statistical analyses were conducted by the authors using AMOS, and all interpretations were independently developed and verified by the authors before being finalized. The authors have reviewed and edited all AI-assisted content and assume full responsibility for the content of this publication.

Table 1. Survey items.

Constructs	Code	Descriptions	Sources
Competence	COM1	I feel that ADC of airline is intelligent	
	COM2	I feel that ADC of airline is skillful	
	COM3	I feel that ADC of airline is clever	
Flexibility	FLE1	ADC of airline is flexible enough to handle the unforeseen problems I encounter with airline services	
	FLE2	ADC of airline can easily adjust its responses to meet my changing needs	
	FLE3	ADC of airline is flexible in responding to the customized requests I make about airline services	
Responsiveness	RES1	ADC promptly addresses my customized requests	
	RES2	ADC of airline efficiently provides proper solutions to fulfill my needs	[9]
	RES3	ADC of airline is earnestly working to provide assistance in need	
Speed	SPE1	Airline's ADC provides a fast and satisfactory reply	
	SPE2	Response provided by ADC of airline is short and efficient	
	SPE3	Airline's ADC provides answers faster than other conversation approaches	
Perceived usefulness	PEU1	I can utilize ADC of airline anytime and anywhere	
	PEU2	Utilizing ADC of airline is convenient	
	PEU3	Utilizing ADC of airline is useful to my airline related activities	

Table 1. *Cont.*

Constructs	Code	Descriptions	Sources
Satisfaction	SAT1	ADC of airline meets my expectations for qualified customer service	[86]
	SAT2	Interactions with airline's ADC leave me with a positive impression of the airline	
	SAT3	ADC of airline contributes to my overall satisfaction as a customer	
	SAT4	Overall, I am satisfied with my experiences with ADC of airline	
Customer Loyalty	CL1	I will go on using this ADC of airline as my first choice	[87]
	CL2	I will recommend this ADC of airline to my friends who seek my advice	
	CL3	I intend to continue using this ADC of airline for a long time	
	CL4	I will say positive things about ADC of airline service to other people.	

5. Results

5.1. Data Analysis

Data collection was conducted using a Google survey distributed across a widely used Korean social media network, yielding 303 responses. Statistical analysis was performed using SPSS (Version 31) for descriptive statistics and internal reliability checking (Cronbach's alpha). AMOS (Version 31) was then used for confirmatory factor analysis (CFA) to verify convergent validity, discriminant validity, and model fit, followed by structural equation modeling (SEM) to evaluate the hypotheses [88,89]. AMOS was also used to run correlation analysis to examine inter-construct correlations prior to model estimation and confirm the data's readiness for SEM [90].

The complete set of 303 samples was utilized in the analysis, which was conducted on the sample covariance matrix. Maximum likelihood estimation assumes multivariate normality and is known to be sensitive to departures from it. Consequently, all inferential tests reported below—including every direct, indirect, and total effect—have been obtained through bias-corrected bootstrapping with 2000 resamples. This procedure derives confidence intervals empirically from the observed data and therefore does not rely on the normality assumption. Throughout the paper, path coefficients are reported as standardized estimates (β), whereas standard errors and critical ratios are based on unstandardized estimates; unstandardized values may exceed 1.00 because the indicators are measured on differing metrics.

5.2. Descriptive Statistics

Table 2 shows the demographic distribution of the 303 respondents. The largest age groups among respondents were those in their 30s at 45% and 40s at 25%, with 91% identifying as Korean nationals. 69% of participants held a bachelor's degree, and 21% held a master's or doctoral degree, indicating a relatively well-educated respondent group.

Over half of the participants, 53%, were employed full-time, while 13% of the participants were self-employed, reflecting a respondent base with stable economic activity and the potential for significant purchasing power in the context of air travel. Korean full-service carriers were preferred by 77% of the surveyed when it came to their travel behaviors.

Table 2. Demographic profile [n: 303].

Constructs	Items	N	%
Age	20–29	31	10
	30–39	137	45
	40–49	75	25
	50–59	35	12
	60–69	19	6
	Over 70	6	2
Country/Region	Korea	276	91
	Other Asia except Korea	19	6
	United states/Canada	5	2
	Europe	3	1
Employment Status	Full-time employee	159	53
	Temporary/contract employee	28	9
	Self-employed	39	13
	Employer	24	8
	Student	21	7
	Homemaker	25	8
	Unemployed/Job seeker	1	0
	Retired	6	2
Education	High school graduate	21	7
	Associate degree	9	3
	Bachelor's degree	209	69
	Master's/Doctoral degree	64	21
Preferred airline type	KR Full service carrier	232	77
	KR Low cost carrier	31	10
	Non KR Full service carrier	37	12
	Non KR Low cost carrier	3	1
Daily Internet usage time	Less than 1 h	18	6
	1–3 h	65	22
	3–5 h	68	22
	More than 5 h	152	50
AI chatbot experience of others	Yes	273	90
	No	30	10

In terms of digital behavior, half of the respondents reported using the internet for more than five hours a day, while 22% spent 3–5 h online. This indicates a high level of digital activities among the participants, which may increase their familiarity with the internet, digital devices and AI-based technologies. Furthermore, 90% of respondents indicated familiar experience with AI chatbots, suggesting that most participants were already exposed to AI-driven interactions and therefore capable of providing informed evaluations regarding ADC in the airline industry. Given this study's focus on how ADC capabilities shape satisfaction and loyalty, this high level of digital familiarity suggests that respondents were well positioned to evaluate ADC performance.

5.3. Confirmatory Factor Analysis

Prior to hypothesis testing, the measurement model was validated using CFA. The model's integrity was assessed through internal consistency, convergent validity, and parameter stability. As illustrated in Table 3, all Cronbach's alpha values ranged from 0.820 to 0.931, substantially exceeding the 0.70 benchmark. Similarly, Composite Reliability (CR) values for all latent variables were above 0.825, confirming high internal reliability across all scales. Convergent validity was further substantiated through Average Variance Extracted (AVE) and Squared Multiple Correlations (SMC). Every latent construct achieved an AVE value greater than 0.612, surpassing the recommended 0.50 threshold. It indicates that the constructs account for a majority of the variance in their indicators. Additionally, SMC values were consistently above 0.488 (with the majority exceeding 0.60), confirming that the observed variables adequately represent their underlying constructs.

Table 3. Confirmatory Factor Analysis.

Indicators		Standardized Factor Loading	Cronbach α	SMC	AVE	CR
Competence	COM3	0.769	0.853	0.591	0.668	0.858
	COM2	0.823		0.678		
	COM1	0.858		0.736		
Flexibility	FLE3	0.867	0.891	0.751	0.734	0.892
	FLE2	0.876		0.767		
	FLE1	0.826		0.682		
Responsiveness	RES3	0.776	0.863	0.602	0.677	0.862
	RES2	0.849		0.721		
	RES1	0.841		0.708		
Speed	SPE3	0.743	0.820	0.551	0.612	0.825
	SPE2	0.826		0.681		
	SPE1	0.776		0.603		
Perceived usefulness	PEU3	0.896	0.860	0.803	0.680	0.863
	PEU2	0.866		0.750		
	PEU1	0.698		0.488		
Satisfaction	SAT4	0.878	0.928	0.770	0.763	0.928
	SAT3	0.875		0.765		
	SAT2	0.868		0.754		
	SAT1	0.875		0.765		
Customer loyalty	CL4	0.878	0.931	0.770	0.777	0.933
	CL3	0.899		0.808		
	CL2	0.911		0.829		
	CL1	0.837		0.700		

Note. N = 303. All loadings significant at $p < 0.001$.

The standardized factor loadings ranged from 0.698 to 0.911, and all of them were statistically significant at the $p < 0.001$ level. Although one loading was marginally below the 0.70 benchmark, it surpassed the more lenient 0.50 threshold recommended for acceptable convergent validity [81]. These results confirm that the observed items reliably reflect their respective latent constructs.

Prior to assessing discriminant validity among the constructs in the research model, it is necessary to clarify the specification of agility capability. At the first-order level, the four agility dimensions were not empirically differentiated: inter-dimension correlations ranged from 0.756 to 0.961, and the HTMT ratio between flexibility and responsiveness approached unity (≈0.96; Appendix A). The elevated values observed among the four dimensions are consistent with the theoretical premise that they constitute complementary manifestations of a single higher-order agility capability rather than empirically distinct constructs, thereby supporting the second-order specification adopted in this study (see Section 3.1.5). Agility capability was therefore specified as a second-order reflective construct. As shown in Table 4, all second-order loadings were significant and substantial (β = 0.870–0.993, $p < 0.001$), and the construct demonstrated sound convergent validity (AVE = 0.861, CR = 0.961). Discriminant validity was accordingly assessed at this higher-order level, employing the square root of its AVE (0.928).

Table 4. Second-order construct of Agility Capability.

First-Order Dimension	Unstd. Estimate	S.E.	t-Value	Std. Loading	AVE	CR
Competence	0.683	0.051	13.324 ***	0.870	0.861	0.961
Flexibility	0.816	0.048	17.128 ***	0.941		
Responsiveness	0.709	0.045	15.617 ***	0.993		
Speed	0.653	0.049	13.206 ***	0.904		

Note. Estimates are derived from the confirmatory factor analysis. *** $p < 0.001$. Estimates are derived from the confirmatory factor analysis. AVE and CR (Composite Reliability) were computed from the standardized second-order loadings. Unstd. Estimate = unstandardized estimate; S.E. = standard error; t-value = unstandardized estimate/S.E.; Std. loading = standardized estimate. Unstandardized estimates may exceed 1.00 because indicators are measured on differing metrics, whereas all standardized estimates lie within the admissible range. *** $p < 0.001$.

Discriminant validity was examined using three complementary criteria. First, based on the Fornell–Larcker criterion, the square root of the AVE for each construct was compared with its inter-construct correlations [90]. As reported in Table 5, all construct pairs satisfied this criterion except for the satisfaction–customer loyalty pair, whose correlation (0.948) exceeded the square roots of their respective AVEs (0.873 and 0.881). Second, discriminant validity was further examined using the heterotrait–monotrait (HTMT) ratio of correlations, computed from the item correlation matrix following [91]. As shown in Table 6, all HTMT values were below the conservative threshold of 0.90, except for the satisfaction–customer loyalty pair (HTMT = 0.948). For this pair, the HTMT-inference criterion [92] was applied: the 95% bootstrap confidence interval (5000 resamples) was [0.918, 0.975], which did not include 1, indicating that the two constructs are empirically distinct. Third, a chi-square difference test [93] showed that a constrained model merging satisfaction and customer loyalty into a single factor exhibited a significantly worse fit than the hypothesized two-factor model ($\Delta\chi^2 = 48.79$, $\Delta df = 3$, $p < 0.001$).

These results provide support for the discriminant validity of the measurement model. While the HTMT-inference criterion and the chi-square difference test both indicate that satisfaction and customer loyalty are statistically distinguishable, the magnitude of their association (r = 0.948) warrants caution: the two constructs, though separable, share a substantial proportion of variance. This pattern aligns with existing service research, in which satisfaction and loyalty are theoretically and empirically closely linked. Accordingly, it suggests that the estimated satisfaction–loyalty path should be interpreted as reflecting a considerable conceptual proximity rather than a purely independent relationship.

Table 5. Discriminant validity.

Constructs	A	B	C	D
Agility Capability	0.928			
Perceived usefulness	0.861	0.825		
Satisfaction	0.895	0.889	0.873	
Customer loyalty	0.852	0.869	0.948	0.881

Table 6. HTMT Criterion for Discriminant Validity.

Constructs	A	B	C	D
Agility Capability				
Perceived usefulness	0.866			
Satisfaction	0.893	0.881		
Customer loyalty	0.850	0.866	0.948	

5.4. Model Fit Indices

Table 7 presents the computed fit indices for this conceptual framework. All the fit indices were satisfactory, with some even exceeding the recommended criteria. The goodness-of-fit indices indicated that the proposed model adequately represents the empirical data (χ^2/df = 1.847, RMR = 0.028, GFI = 0.900, AGFI = 0.870). The incremental fit indices (NFI = 0.942, CFI = 0.972, RMSEA = 0.053) were within the recommended thresholds. Since all other indices satisfied their recommended criteria, the overall model fit was considered acceptable. These results indicate that the measurement model aligns with the established criteria for goodness-of-fit based on [81,94].

Table 7. Model fit results.

Division		Result	Acceptance Level	Reference
Absolute fit index	CMIN/DF	1.847	$\leq$3.0 or 1 < χ^2/df < 3	[81,94]
	RMR	0.028	$\leq$0.05	
	GFI	0.900	$\geq$0.90	
	AGFI	0.870	$\geq$0.80	
	RMSEA	0.053	$\leq$0.08	
Incremental fit index	NFI	0.942	$\geq$0.90	
	CFI	0.972	$\geq$0.95	

5.5. SEM (Structural Equation Modelling) Analysis

SEM results showed that all the hypothesized relationships from Hypotheses H1 to H4 were statistically significant, with t-values (C.R.) exceeding the 1.96 threshold ($p < 0.001$). The overall structural model demonstrated sufficient explanatory power within the theoretical framework. Table 8 illustrates the conceptual framework alongside the path analysis outcomes, while Figure 2 maps these relationships visually. Figure 2 depicts all four hypothesized direct paths that are significant. The results traced a sequential chain from agility capability to customer loyalty. Agility capability first shaped customers' cognitive evaluation, exerting a strong effect on perceived usefulness (β = 0.869, SE = 0.045, t-value = 15.966, $p < 0.001$). It then influenced satisfaction through two routes: directly (β = 0.526, SE = 0.070, t-value = 6.284, $p < 0.001$) and indirectly via perceived usefulness, which significantly predicted satisfaction (β = 0.439, SE = 0.083, t-value = 5.266, $p < 0.001$). Satisfaction was found to have a strong correlation with customer loyalty (β = 0.946, SE = 0.135, t-value = 7.279, $p < 0.001$).

Table 8. Hypotheses path analysis results.

No	Hypotheses			β (Std. Coef.)	S.E	t-Value	*p*	Results
H1	Agility capability	→	Perceived usefulness	0.869	0.045	15.966	***	Supported
H2	Agility capability	→	Satisfaction	0.526	0.070	6.284	***	Supported
H3	Perceived usefulness	→	Satisfaction	0.439	0.083	5.266	***	Supported
H4	Satisfaction	→	Customer loyalty	0.946	0.135	7.279	***	Supported
Additional path	Agility capability	→	Customer loyalty	−0.079	0.085	−0.807	0.420	Not significant
Additional path	Perceived usefulness	→	Customer loyalty	0.089	0.096	0.964	0.335	Not significant
No	Hypotheses			Indirect Effect	95%BC CI		*p*	Results
H5	Agility capability → Customer loyalty (via Perceived usefulness and Satisfaction)			0.936	[0.758, 1.200]		***	Supported
H6	Perceived usefulness → Satisfaction → Customer loyalty			0.415	[0.179, 0.786]		***	Supported

Note. β = standardized path coefficient; S.E. and C.R. (critical ratio) are based on unstandardized estimates. Bootstrap confidence intervals are bias-corrected (2000 resamples). *** $p < 0.001$. Indirect effects are reported as standardized estimates with 95% bias-corrected bootstrap confidence intervals. The additional paths from agility capability and perceived usefulness to customer loyalty were not hypothesized; they were freely estimated so that the type of mediation could be formally assessed following Zhao et al. [95]. Their non-significance supports the fully mediated structure proposed in H5.

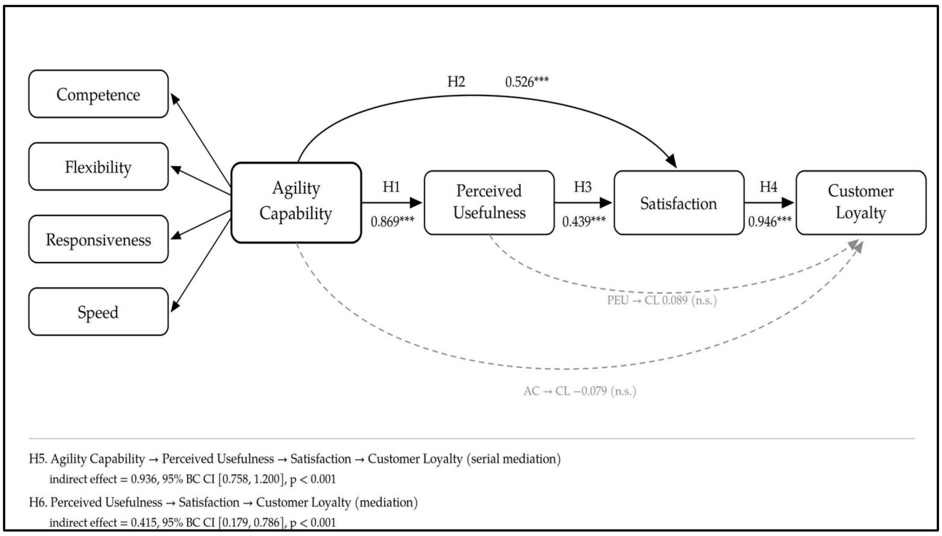

Figure 2. SEM analysis results. Note. *** $p < 0.001$; n.s. = not significant.

Direct paths from agility capability and perceived usefulness to loyalty were additionally estimated but were non-significant (β = −0.079, $p = 0.420$; β = 0.089, $p = 0.335$, respectively), indicating that satisfaction was the sole proximal predictor of loyalty.

5.6. Mediation Analysis

Bias-corrected bootstrapping (2000 resamples, 95% CI) was conducted to test the indirect mechanisms. The indirect effect of perceived usefulness on customer loyalty through satisfaction was significant (β = 0.415, 95% BC CI [0.179, 0.786], $p = 0.001$), as was the indirect effect of agility capability on satisfaction through perceived usefulness (β = 0.381, 95% BC CI [0.166, 0.620], $p = 0.001$). The total indirect effect of agility capability on customer loyalty was also significant (β = 0.936, 95% BC CI [0.758, 1.200], $p = 0.001$). Combined with the non-significant direct effects on loyalty, this indicates that agility capability is transmitted to loyalty entirely through perceived usefulness and satisfaction in sequence, supporting H5. Likewise, the significant indirect effect of perceived usefulness on loyalty through satisfaction, coupled with its non-significant direct effect, supports H6.

To classify the mediating role of perceived usefulness in the agility capability–satisfaction relationship, this study employs the analytical typology proposed by Zhao et al. [95]. The direct effect of agility capability on satisfaction remained significant (H2: β = 0.439, $p < 0.001$), and, as reported above, the indirect effect through perceived usefulness was likewise significant with a confidence interval excluding zero. Because both the direct and indirect paths were significant and shared the same sign, the results indicate complementary mediation rather than full mediation. This suggests that agility capability enhances satisfaction not only directly but also partly by improving customers' perceived usefulness of the ADC, with a meaningful portion of its influence transmitted through this cognitive evaluation. Therefore, the mediation pattern differs by outcome: perceived usefulness complementarily mediates the effect of agility capability on satisfaction, whereas the effect of agility capability on customer loyalty is fully mediated by perceived usefulness and satisfaction in sequence.

6. Discussion

6.1. Theoretical Implications

The findings position the airline ADC's agility capability, modeled here as a second-order construct, as the foundational antecedent of the entire service-outcome chain. Agility capability exerts a strong direct effect on perceived usefulness (β = 0.869, $p < 0.001$), confirming that a coherent, prompt, responsive, and competent conversational agent is first and foremost experienced as useful. The integrated capability shapes the passenger's perception of how instrumentally valuable airline ADCs are.

Satisfaction emerges as the pivotal construct in the model, jointly shaped by two antecedents. Agility capability directly contributes to satisfaction (β = 0.526, $p < 0.001$), while perceived usefulness contributes to satisfaction even more strongly (β = 0.439, $p < 0.001$). This dual pathway indicates that the ADC's inherent capability itself directly contributes to satisfaction beyond its instrumental value, suggesting that satisfaction is not solely a by-product of perceived usefulness. In other words, passengers are satisfied with the ADC not only because it proves useful, but because it responds in an agile and capable manner while resolving their travel queries.

The most theoretically consequential result is the full-mediation pattern surrounding customer loyalty. Neither agility capability (β = −0.079, $p = 0.420$) nor perceived usefulness (β = 0.089, $p = 0.335$) exerts a significant direct effect on loyalty. Instead, satisfaction is the sole significant driver of loyalty (β = 0.946, $p < 0.001$) and fully carries the influence of the upstream constructs. The bootstrapped indirect effects confirm this mechanism: agility capability reaches loyalty only through the mediating sequence of perceived usefulness and satisfaction (β = 0.936), and perceived usefulness reaches loyalty only through satisfaction (β = 0.415). Theoretically, this establishes satisfaction as an indispensable affective gateway: agility capability and perceived usefulness are necessary upstream conditions, but they alone are insufficient to ensure behavioral commitment. Its antecedents must first pass through the customer's holistic evaluation of the experience.

These dynamics may be further elucidated considering the sample's characteristics. 90 percent of respondents are familiar with ADCs and display a high level of digital fluency. In the aviation industry, accurate and high-quality resolution is critical for maintaining customer satisfaction and sustained loyalty. This emphasis on dependable resolution builds a solid relationship with customers and keeps them returning to the airline's digital ecosystem.

The theoretical framework of this study extends the existing literature in the following ways. First, it extends established technology-adoption frameworks—specifically TAM and

ECT—into the under-researched domain of airline IT infrastructure. Whereas prior studies have focused heavily on front-end consumer applications such as mobile booking apps and kiosks, this research is among the first in the South Korean context to empirically examine how ADCs influence the traveler experience. Second, by conceptualizing agility capability as a second-order construct and demonstrating a fully mediated mechanism in which satisfaction is the exclusive conduit to loyalty, the study delineates a clear structural route by which the agility capability of an ADC is converted into sustained customer loyalty.

6.2. Managerial Implications

From a practical perspective, the findings offer concrete guidance for industry executives navigating rapid digital transformation. First, this study provides a strategic roadmap for airline executives and customer-service or IT directors when allocating resources. Because agility capability functions as an integrated construct, managers are advised to invest in its dimensions as a coherent whole rather than optimizing any single feature in isolation. Aligning IT investment with the agility capability of ADCs directly strengthens perceived usefulness and satisfaction, laying the groundwork for sustainable service quality.

Second, the findings highlight that customer loyalty is secured only when the ADC's capability is converted into genuine satisfaction. Agility capability and perceived usefulness influence loyalty exclusively through satisfaction. Technology is not merely deployed, but rather experienced and valued by customers. To that end, airlines should implement proactive, real-time feedback and support mechanisms that translate complex operational data into immediate, responsive communication—the behavioral core of agility capability. Such interactive ADCs can reduce the anxiety associated with air travel and enhance perceived traveler value, thereby strengthening long-term commitment. This is consistent with evidence that AI-driven technologies improve customer experience and value in the travel industry [95].

6.3. Limitations

Despite the insights of this study, several limitations must be acknowledged.

First, this study relies on cross-sectional, self-reported survey data. Accordingly, the findings capture passengers' perceptions and behavioral intentions at a single point in time rather than actual behavior or objective financial outcomes. Endogeneity cannot be excluded, as unobserved respondent characteristics may jointly influence perceived agility and the evaluative outcomes. A formal assessment such as the Gaussian copula [96] approach was not conducted because it presumes non-normally distributed exogenous regressors, a condition not satisfied by the present Likert-scale indicators. Therefore, the structural model's causal directions implied by the structural model should be interpreted as theoretically grounded associations rather than established causal effects. Additionally, the conclusions are confined to perceived usefulness, satisfaction, and loyalty intentions.

Second, the sample was heavily concentrated within the Korean market. While this provides deep insights into the Korean consumer's experience, it may limit the generalizability of the findings to different regional contexts. The behavioral patterns of ADC usage may differ across markets, and the relative contribution of each dimension to the overall agility capability construct could vary in Western or other Asian contexts. As a result, the way agility capability influences perceived usefulness and satisfaction may vary across different cultural settings.

Third, 90% of respondents had experience with ADCs in other industries. This sample was also concentrated among respondents aged 30–49, whose high level of digital familiarity may further limit the generalizability of the findings to broader age groups. Given their high digital literacy, these respondents may exhibit a lower tolerance for system delays and higher expectations for immediate engagement. This characteristic may have shaped how the underlying dimensions come together to form the overall agility capability construct, potentially amplifying the weight of responsiveness-related aspects in that formation.

Fourth, the scope of this research was confined to a specific sector within the digital landscape of the airline industry. Given the variability of service quality dimensions across different industries [97], it is important to carefully consider how to prioritize the variables in agility capability. In addition, recruitment relied on convenience sampling through social media, which may limit the generalizability of the findings. Future research employing probability-based sampling would enhance external validity.

Fifth, perceived value was initially examined as an outcome variable in this study. However, it could not be empirically distinguished from customer loyalty ($r = 0.994$; HTMT = 1.000) and was therefore excluded from the final model. Future research should measure this construct using behavioral or financial indicators, such as repurchase frequency or revenue contribution.

Finally, satisfaction and customer loyalty exhibited a very high correlation (0.948). Although formal tests supported their distinctiveness, the strong path from satisfaction to loyalty ($\beta = 0.946$) should be interpreted with this overlap in mind. Employing behavioral loyalty measures including observed repurchase or referral patterns would provide a sharper separation between affective satisfaction and behavioral commitment.

6.4. Future Research Directions

Future research should complement perceptual measures with objective performance data. Longitudinal or panel designs, combined with airline-side operational and financial records—such as actual repurchase behavior, service-channel cost data, and customer lifetime value—would allow the satisfaction–loyalty–profitability linkage, which could not be tested in the present model, to be examined with objective outcomes rather than perceptions alone.

Experimental or multi-wave designs would also strengthen causal inference regarding the effect of ADC agility capability on downstream outcomes. Additionally, it would serve to mitigate the endogeneity concerns inherent in single-source cross-sectional data. In circumstances where observational designs are unavoidable, instrumental-variable estimation—or the Gaussian copula approach applied to indicators meeting its distributional requirements—would permit a formal test of regressor exogeneity.

Subsequent research needs to conduct cross-cultural or multinational comparative studies to address this geographic constraint. Such comparisons would validate the global applicability of these findings and identify universal patterns of customer behavior by replicating this research model in regions with differing cultural dimensions and market structures. Succeeding studies should endeavor to obtain a more demographically diverse sample by recruiting international participants across a broader range of age groups, socioeconomic backgrounds, and digital proficiency levels. An exploration of the influence of digital literacy on the relationship between agility and perceived usefulness would provide a deeper view of the digital background.

To address this industry-specific limitation, future research should broaden the empirical scope by testing this framework across a wider array of digital service industries. Comparative analyses between highly transactional sectors and highly risk-sensitive sectors would clarify whether the influence of agility capability on customer outcomes is universal, or whether it is contingent upon the specific nature and perceived risk of the digital service.

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7. Conclusions

In conclusion, this study investigated the relationship between the agility capability of airline ADCs and its impact on perceived usefulness and satisfaction, as well as the subsequent effect on customer loyalty. The results demonstrate that satisfaction serves as the pivotal conduit between technological capability and behavioral commitment. In this sense, the agility capability of the airline industry satisfies customer demands by enabling digital service innovations and the convergence of hospitality and advanced IT as a driver of adaptability and competitiveness [23]. As airlines accelerate their digital transformation, this capability distinguishes itself as a strategic asset that converts advanced IT into a satisfying and ultimately loyalty-building experience. It provides both a theoretical foundation and actionable direction for airlines seeking sustainable competitiveness in an increasingly AI-driven service landscape. While these limitations highlight important boundaries of the current study, they also map out a clear and valuable track for subsequent research in the agility capability of ADCs. By addressing these geographic, demographic, and industrial constraints, subsequent studies can build upon the foundational insights established in this work. Ultimately, this study makes a significant contribution to the development of a more robust, globally applicable framework for understanding airline customers' priorities and experiences in the digital age.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions arising from the consent obtained from survey participants.

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Abbreviations

The following abbreviations are used in this manuscript:

ADC	AI-Driven chatbots
AI	Artificial Intelligence
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis

CI	Bias-corrected bootstrap confidence interval
PEOU	Perceived Ease of use
PU	Perceived Usefulness
CR	Composite Reliability
C.R.	Critical Ratios
ECT	Expectation-Confirmation Theory
HCI	Human–Computer Interaction
IS	Information System
NLP	Natural Language Processing
SEM	Structural Equation Modeling
SMC	Squared Multiple Correlations
SPC	Service-Profit Chain theory
TAM	Technology Acceptance Model

Appendix A

Table A1. Heterotrait–monotrait (HTMT) ratios among the four first-order dimensions of agility capability.

Construct	1	2	3	4	5	6	7
1. Competence	-						
2. Flexibility	0.884	-					
3. Responsiveness	0.841	0.955	-				
4. Speed	0.76	0.783	0.915	-			
5. Perceived usefulness	0.753	0.755	0.826	0.931	-		
6. Satisfaction	0.801	0.832	0.869	0.857	0.881	-	
7. Customer loyalty	0.757	0.804	0.844	0.791	0.866	0.948	-

Note. HTMT values were computed following Henseler et al. [91]. Values approaching or exceeding conventional thresholds indicate that the four dimensions are not empirically distinct at the first-order level, supporting their specification as reflective indicators of a second-order agility capability construct.

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