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Understanding Consumer Buying Intention of E-Commerce Airfares Based on Multivariate Demographic Segmentation: A Multigroup Structural Equation Modeling Approach

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Abstract: The internet offers enormous development opportunities for airline firms and a lot of information for consumers to pick the finest available options. This research aims to study the consumer buying intention of e-commerce airfares in an emerging economy based on the technology acceptance model. This article employed a sample of 3064 respondents at six airports in Thailand. It used cluster analysis (a multivariate analysis approach) to determine two main customer segments and then used a structural equation modeling (SEM) technique utilizing demographic segmentation as a moderator to explain the behaviors of those two segments. The findings demonstrated two customer segments: (1) the older with high and middle-income segment, and (2) the young with low-income segment. The empirical results revealed that price sensitivity and perceived ease of use substantially impacted behavioral intention to use e-commerce airfares in both segments. The users from segment (1) are more likely to look for the fun experience and entertainment value of using e-commerce airfares than those from segment (2). However, perceived usefulness is unlikely to be a vital factor in consumers' purchasing decisions about using e-commerce airfares. It is recommended that airline companies and online travel agencies should consider perceived ease of use, price sensitivity, and hedonic motivation when implementing e-commerce airline websites for selling tickets.

Keywords: technology adoption; technology acceptance model (TAM); e-commerce; airline industry; multivariate demographic segmentation

Citation: Naruetharadhol, P.; Wongsaichia, S.; Zhang, S.; Phonthanukitithaworn, C.; Ketkaew, C. Understanding Consumer Buying Intention of E-Commerce Airfares Based on Multivariate Demographic Segmentation: A Multigroup Structural Equation Modeling Approach. *Sustainability* **2022**, *14*, 8997. https://doi.org/10.3390/su14158997

Academic Editor: Javier Faulin

Received: 17 June 2022
Accepted: 21 July 2022
Published: 22 July 2022

1. Introduction

Over the past two decades, there has been a rapid evolution in airplane ticket reservations since the development of information technology has prompted the travel industry to seek a more modern approach to conducting business [1]. Additionally, the high acceptance of e-commerce has become a significant component for hospitality industries in adopting constructive e-commerce channels [2]. Therefore, the online distribution of the tourism section, involving flights, hotel rooms, travel packages, cruises, and car rentals, has utilized the benefits of technology and electronic devices to build a strong relationship with customers and make profits at the same time [3]. Meanwhile, with the increasing demand and competition in the airline industry triggered by the COVID-19 pandemic, the airline company should understand passengers' buying intentions every day. Currently, online air travel reservations are the typical method for travelers. The tourism industry is evaluated to be worth about $1.2 trillion annually, and the online reservation market accounts for 63% of that, or approximately $756 billion, which represents one of the sector's most significant market shares. Considering that online booking is worth $817 billion, the market will grow by 8% in 2020 [4].

Aircraft seat reservation has been overcoming many challenges to make booking fast, convenient, and operationally easy. Weng et al. [5] claimed that consumers mostly preferred to adopt mobile applications that are generally smoother and easier to navigate than mobile-friendly websites, which deliver fast experiences while using online booking. Those who preferred mobile applications were satisfied by numerous unique features such as quickness of booking (39%), extra functionality (30%), and price alert notifications (79%). Millennials, who prefer convenience, are much more focused on reducing time spent on reserving airline tickets. Hence, several airlines and travel agencies provide e-ticketing and online booking in response to passengers' demands. Moreover, an estimated 700 million people will utilize an online reservation system by 2023 [4]. Kunst [6] indicated that 43% of 18 to 29 years old reserve flights online instead of at a travel agency or a counter in the UK. However, there are 37% and 27% for 30 to 59 year-olds and 60 year-olds and above.

There were 48.59 million internet users in Thailand in January 2021, and the number of internet users in Thailand increased by 3.4 million between 2020 and 2021 [7]. It has been predicted that it will still expand in the years ahead with the fast enhancement of internet access. The increasing acceptance and popularity of the internet and e-commerce provides convenience for ticket reservation approaches [8]. Thai travelers use the internet to explore information in arranging their travel destinations, booking accommodations, renting cars, reserving restaurants, and purchasing package tours [9]. According to a survey by Statista [10], 51% of the Thai travelers expressed that they have utilized an online travel agency, 41% of the travelers expressed that they had not, and only 8% claimed that they do not know what an online travel agency is.

Furthermore, the internet offers massive prospects for growth for airline companies and an abundance of information for purchasers to select the best available choices. The advantages of e-commerce are that it reduces costs and provides opportunities for enhancing operations and customer service. The airline sector adopts the success of e-commerce and technology to recreate the business structure. Business travelers are likely to employ internet travel agencies to reserve their tickets faster and more conveniently [11]. The improvement of information technology helps the airline sector to expand into global markets. It brings an essential change to the airline sector regarding the distribution channels. To develop their businesses and tailor online services based on customer needs, airline companies must comprehend how e-commerce experiences are related to customers in different segments.

This study aims to identify the factors influencing consumer buying intention of e-commerce airfares based on multivariate demographic segmentation. In this case, this paper uses multivariate demographic segmentation, entailing the use of two demographic characteristics (age and income) in combination with one another and employs a multigroup structural equation modeling analysis to deeply explain the behaviors of the customers in each segment. Additionally, the research framework was founded on the technology acceptance model [12], which was then extended to be relevant to the study context.

2. Literature Review

2.1. The Technology Acceptance Model

Davis [12] established the Technology Acceptance Model, consisting of perceived usefulness, perceived ease of use, behavioral intention, and use behavior. According to Davis [12], the Technology Acceptance Model was originally intended to give an explanation of the factors influencing computer acceptance that could account for user behavior across a wide range of end-user computing technologies. Over the last few decades, the Technology Acceptance Model and its efficacy have been tested for numerous IT applications.

However, this research employed an extended Technology Acceptance Model. Recent studies have revealed that it enables us to add more factors to the original model in order to investigate an individual's technology acceptance in a given setting more thoroughly [13,14].

For instance, Kamal et al. [13] investigated the acceptance of telemedicine services by adding more variables, such as perceived risk, privacy, and resistance to technology, to the analysis. Sukendro et al. [14] also added a variable, facilitating condition, to investigate students' use of e-learning during COVID-19.

Thus, in this study, we employed an extended Technology Acceptance Model. In addition to the original variables, we added price sensitivity and hedonic motivation to the model. Especially during pandemics, it is interesting to examine how price sensitivity may demonstrate how buyers feel about pricing and price variations and how hedonic motivation may drive internet search and buying intention. Additionally, as this study focused solely on perceptions prior to the purchase of airfares, no actual purchase behavior was taken into account. Hence, this paper aimed to apply five constructs of the extended Technology Acceptance Model (perceived usefulness, perceived ease of use, price sensitivity, hedonic motivation, and behavioral intention) to study the consumer buying intention of e-commerce airfares based on demographic segmentation.

2.1.1. Perceived Usefulness

Perceived usefulness was defined as the level at which technology will prepare customers to execute specific activities [15–17]. In other words, perceived usefulness is the degree to which a person thinks using a certain technology would be useful [18]. Perceived usefulness is a significant component of the behavioral intention to utilize technology. As for mobile applications, if users realize values and innovations from the mobile applications, they are more inclined to buy and use the mobile applications [19]. Naruetharadhol et al. [20] conducted a survey among e-banking customers in Thailand and revealed that perceived usefulness significantly influences customers' behavior intention. However, Tahar et al. claimed that perceived usefulness was not a significant predictor of employing e-filing services [21]. In sum, the relationship between perceived usefulness and behavioral intention needs to be explored empirically.

Hypothesis 1 (H1). *Perceived usefulness will positively affect behavioral intention to use e-commerce airfares*.

2.1.2. Perceived Ease of Use

Perceived ease of use is described as the degree of ease related to the utilization of a technology [12]. It is frequently acknowledged as a significant predictor of a user's behavioral intention [22]. Park and Ohm [23] indicated that the user-friendliness of mobile apps positively affected the utilization of mobile apps as a lesser attempt is needed to employ the apps. Previous research claimed that service convenience significantly influenced customers' behavioral intentions in e-retailing circumstances [24]. Bilgihan et al. [25] suggested that perceived ease of use was an essential factor in tourism information systems research. It is related to users' assessment of the effort required to develop technology because convenience is one of the most standard motivations for buyers to shop online [26,27]. Consumers perceive online purchasing convenience as essential to online business accomplishment [28]. In online travel circumstances, users enjoy the convenience of using online platforms when comparing prices, saving time, searching for a travel destination, and booking hotel rooms and flights [29]. As such, a website should offer user-friendly interfaces and features to aid users in finding what they need quickly and easily [30].

Hypothesis 2 (H2). *Perceived ease of use will positively affect behavioral intention to use e-commerce airfares*.

2.1.3. Price Sensitivity

Price sensitivity is described as the scope of consciousness and response exhibited by customers when discovering differences in the prices of goods and services [31]. Anderson [32] suggested that price sensitivity was the range in which a purchaser gains price growth for merchandise in terms of economic and psychological benefits. Highly price-sensitive consumers will search for lower prices than consumers who are less price-sensitive [33]. Price sensitivity is a factor that analyzes individual differences and is described as how purchasers feel about prices and price changes [34]. Price has indicated its notable effect on customers' assessment of goods options and their terminal purchasing decision [35–37]. Highly price-sensitive consumers critically consider pricing strategies before making a buying decision on the product. The cost and pricing composition may have a substantial effect on customers' technology utilization. For example, there is confirmation that the popularity of short messaging services (SMS) in China is because SMS's low pricing is associated with other kinds of mobile internet applications [38]. Natarajan et al. [39] demonstrated that price sensitivity is one of the principal elements that influence mobile shopping applications and the whole area of e-commerce to implement differential pricing strategies. In India, the price of commodities plays a crucial role in the purchasing decision of the individual. Tak and Panwar [40] stated that consumers use mobile shopping apps to save money. Thereby, e-commerce shopping platforms consistently offer enormous discounts to consumers for commodities and services.

Hypothesis 3 (H3). *Price sensitivity will positively affect behavioral intention to use e-commerce airfares.*

2.1.4. Hedonic Motivation

Hedonic motivation was described as the pleasure or enjoyment acquired from employing technology [16,41]. The finding of previous research demonstrated that hedonic motivation was the second most significant factor of behavioral intention after habit [42]. Additionally, several papers recommended that hedonic motivation positively impacted technology acceptance and use [41,43]. Salimon et al. [44] suggested that entertainment is a dominant instrument adapted to expand e-banking customers. It appears to them that online banking customers want to enjoy themselves while transacting on the internet. Thus, they encourage a different banking channel that equips underground music and other extra features to interact with the devices suitably. Wagner et al. [45] demonstrated that hedonic motivation is essential for internet-authorized television shopping since it occurs in the family environment with a relaxed perspective, involving enjoyment with shopping intentions. Hedonic motivation directly affects the intention to search for information [46]. Hedonic values would generate search intention and purchase intention of online platforms by providing entertainment and enjoyment.

Hypothesis 4 (H4). *Hedonic motivation will positively affect behavioral intention to use e-commerce airfares.*

2.1.5. Behavioral Intention

Behavioral intention refers to the extent to which an individual has prepared conscious objectives regarding whether to conduct a specified future behavior [47]. It is crucial to apprehend that behavioral intention does not necessarily define actual behavior in people. However, there is a strong correlation between behavioral intention and actual behavior. It is assumed that behavioral intention precedes behavior [47]. Perceived usefulness and trust play crucial roles in determining behavioral intention to embrace mobile commerce [48]. Alalwan et al. [49] also revealed that perceived ease of use, perceived risk, and perceived usefulness positively impacted users' behavioral intention to use mobile banking in Jordan. Their behavioral intention was affected by performance expectancy, effort expectancy, social influence, and facilitating conditions in near-field communication services on cell phones [50]. Casey and Wilson-Evered [51] recommended that both performance expectancy and effort expectancy significantly affect behavioral intention to employ online platforms concerning household arguments. Additionally, social influence strongly influenced behavioral intention in adopting mobile learning [52]. According to previous literature [47–52], behavioral intention can be influenced by many independent variables. Hence, the choice of dependent variables would depend on the theory used and each research setting. Moreover, since this study was primarily concerned with perceptions prior to the purchase of flights, actual purchasing behavior was not taken into consideration.

Therefore, taking into account the literature reviews and the established hypotheses, Figure 1 demonstrates the conceptual model of this study. Additionally, Table 1 reveals the variables, measures, and their definitions.

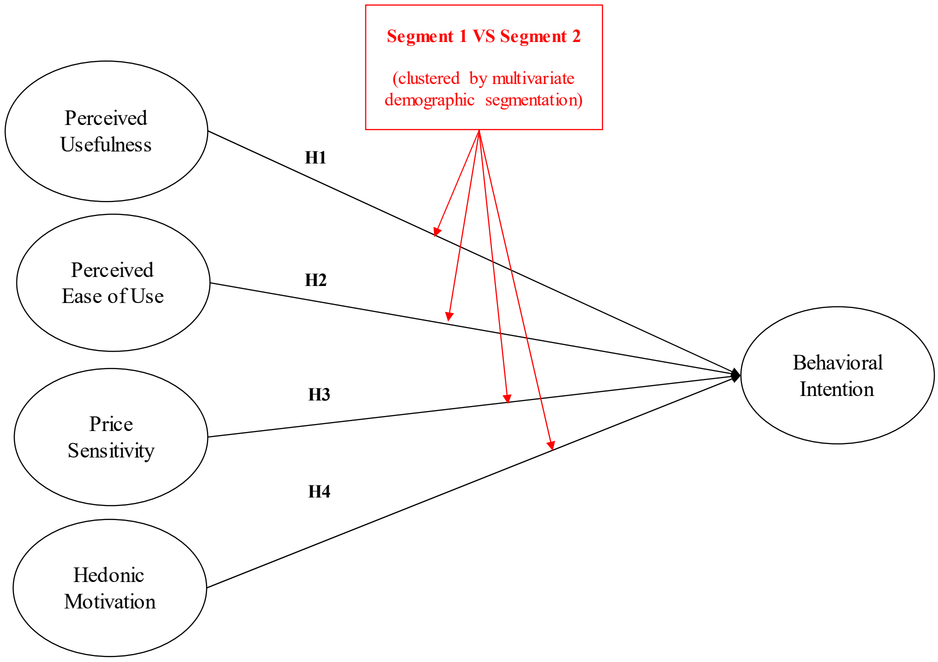

Figure 1. Proposed Model. Source: Figure created by Authors (2021).

Table 1. Variables, Scale, and Measures.

Variable Constructs	Indicators	Definitions	Source/Reference
Perceived Usefulness	PU1 PU2 PU3	Perceived usefulness was defined as the level to which utilizing technology will prepare customers to execute specific activities.	[12,15,16]
Perceived Ease of Use	PE1 PE2 PE3	Perceived ease of use is described as the degree of ease related to the utilization of technology.	[12]
Price Sensitivity	PS1 PS2 PS3	Price sensitivity is described as the scope of consciousness and response exhibited by customers when discovering differences in prices of goods and services.	[31]
Hedonic Motivation	HM1 HM2 HM3	Hedonic motivation was described as the pleasure or enjoyment acquired from employing a technology.	[6,16,39]
Behavioral Intention	BI1 BI2 BI3	Behavioral intention refers to how an individual has prepared conscious objectives regarding whether to conduct a specified future behavior.	[47]

Note: See the abbreviations (PE1, PE2, PE3, . . . , BI3) from Appendix A (Questionnaire). Source: Data adapted from Authors (2021).

2.2. Generations and E-Commerce Airfares

Age has been demonstrated to be a determining component in consumer acceptance of online shopping and customers' behavioral intention [53–55]. However, Schewe et al. [56] recommended generational cohorts as a more professional approach to segmenting markets than just by age. The generation segment offers an in-depth understanding of customer stimulations that emerge from expected values and beliefs [56–58]. Additionally, people of different generations demonstrate diverse purchasing power. Nevertheless, less research has been studied on the significant differences between the generation segment and e-commerce airfares. Therefore, in order to fill up this research gap, this study employed the market segment as a moderator and used the structural equation modeling (SEM) approach to analyze the factors influencing the customer purchase intention of e-commerce airfares. The market segment was analyzed using demographic segmentation, primarily using generations and income variables.

3. Materials & Methods

3.1. Sampling and Data Collection

Data in this study were purposively collected from regular airline passengers in Thailand. The quota and purposive sampling approaches were used in data collection via a structured questionnaire, and the obtained data remained confidential. The constructs employed in this research were measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The study comprises quota respondent proportions from the total population. This approach can be considered a sampling technique for collecting representative data from a group [59]. It is required to focus on a chosen population to accomplish the survey utilizing quantitative approaches [60]. The quota sampling approach was utilized to choose an equal proportion of Thai passengers (600 respondents) from each of the six selected international airports in Thailand, namely Suvarnabhumi Airport, Don Mueang International Airport, Chiang Mai International Airport, Udon Thani International Airport, Hat Yai International Airport, and Phuket International Airport, totaling 3600 respondents as the planned number. The purposive sampling approach was used because only the airline passengers or people utilizing the airline industry services in Thailand and the subjects under inspection were chosen. The data collection was based on the intercept survey conception to gather on-site perception information from respondents in the selected airports' public areas. This technique allows the respondent to accomplish the questionnaire in one go. Therefore, the quality of feedback is increased by less distraction [61]. The research focused only on individuals above 20 years old in Thailand. The questionnaire was derived from the constructs as demonstrated in Table 1.

For the sample size, Hair et al. [62] recommended that no specific rule be adapted in establishing a particular sample size for confirmatory factor analysis (CFA), which is the earliest stage for executing structural equation modeling (SEM). Tabachnick and Fidell [63] proposed that CFA was tactful to sample size and could be less stable when assessed utilizing a small sample. Kline [64] suggested a standard sample size for an SEM study of 200 observations. On the other hand, Hair et al. [62] advised a minimum sample size of 300 when a structural model relates to fewer than seven constructs. Hence, the researchers planned to gather the data based on a structured questionnaire acquired via intercept surveys of 3600 respondents. Nevertheless, we were able to collect data from 3100 respondents from the airports during the COVID-19 pandemic, and only 3064 valid responses were chosen.

In this study, demographic segmentation was used as a moderator along with the structural equation modeling (SEM) approach. Generation X represents the people born between 1960–1979, one of the most highly educated generations [65]. This generation is highly sophisticated in purchasing behavior by seeking promotions [66]. Generation X has a perspective on risk avoidance [67]. Thus, they need reassurance before purchasing their product choices by researching and reviewing more opinion sites than any other generation [68]. Generation Y, or millennial, represents individuals born between 1980–1994. This generation is technologically savvy and engages in online purchase behaviors [69]. Generation Y has taken online shopping as an entertainment or experience aspect [70]. They are more aware of marketing schemes. Therefore, they often compare the best available product choices [71]. Generation Y might be considered impulsive buyers since they make decisions faster than other generations [72]. Generation Z represents the persons born between 1995–2010. This generation are digital natives and depend on technology and electronic devices [73]. They are willing to pay a premium price for personalized commodities and services. Generation Z has been brought up with the internet, so they prefer to purchase products online more than other generations. Additionally, when this generation grows older and their income expands, they will generate strong e-commerce growth in the future [74]. The age of the "Boomer" generation [75] can be calculated to be 58 years or older. Still, mankind's average functioning remains relatively high until the age of 60 years, when an underlying slow rate of decline accelerates [76]. In contrast, the majority of airlines require health certificates from hospitals or medical centers prior to flying for seniors aged 65–75 years or older, which makes the elderly a very small portion of the e-commerce airfare consumer base with low data representation. Therefore, this study only includes generations X, Y, and Z. Based on the characteristics of generations X, Y, and Z, especially in terms of consumption behavior mentioned above, the data was grouped up into generations X, Y, and Z to indicate the moderator.

3.2. Data Analysis

The researchers performed a multivariate clustering analysis using the age and income of the respondents. Then, we performed a *t*-test between two clusters to identify whether any differences existed among the clusters with different solutions [77]. As a follow-up approach, a collection of chi-square tests was employed to validate any significant differences between the clusters in terms of demographic and psychographic segmentation. This study utilized three-step cluster analytic techniques. The first step was hierarchical cluster analysis, which established clusters by escalating within-group similarities and between-group differences [78]. Second, centroid cluster analysis verified the hierarchical cluster solution. Third, squared Euclidean distance was used to minimize the average of the squared distances between observed and estimated values [79].

Before examining the data employing SEM, we addressed common method variance (CMV) in this study. CMV occurs when variables in the same model are tested using the same approach or derived from the same source, which results in systematic error variances among those variables and possibly biases the assessed relationships [80]. This study collected both dependent and independent variables from the same respondents, revealing a CMV risk. We adapted Harman's single factor test following Podsakoff et al. [80] to examine CMV in this research. The results exposed the cumulative variance of 49.387 percent (less than the 50 percent threshold), which further guaranteed the absence of CMV.

Furthermore, this research used the structural equation modeling (SEM) technique through the AMOS statistics program [81]. AMOS is built to analyze data using the covariance-based SEM (CB-SEM) approach, which is more suitable for analyzing data with a large sample size than the partial least square SEM (PLS-SEM) approach when assuming multivariate normality [81]. In this research, the sample is large (n = 3064) and multivariate normality is assumed (Kurtosis values between 0.083 and 0.719 < 3.0). Hence, the selection of AMOS and CB-SEM is justified.

The SEM technique was adopted to assess the model's evaluation in three stages. First, confirmatory factor analysis (CFA) was performed to test each indicator and variable's relationship. Second, the structural model was conducted to measure the entire structure, including estimating the goodness of fit (GOF). Third, multigroup moderation analysis was employed to study the segment's moderating effect on the structural relationship. This stage conducts a measurement invariance (MI) analysis employing segment as a moderator, dividing the sample into two groups (the older with a high- and middle-income segment and the younger with a low-income segment). The results of the statistical analysis are discussed in detail below.

4. Results

4.1. Step 1: Cluster Analysis

From the *t*-test result, it was found that most of the respondents in segment 1 were from generation X. The majority of those respondents earn a monthly income level of more than 25,000 baht in segment 1. In segment 2, most of the respondents were generation Y with a monthly income level of less than 25,000 (Table 2). The findings summarized that consumers were divided into two segments: (1) the older with the high and middle-income segment, and (2) the young with the low-income segment. Table 3 reveals the *t*-test results comparing the customers' perceptions of the two segments. The results show that the mean scores of perceptions between the two segments are statistically different at a <0.01 significance level. In most cases, the mean scores of perceptions of segment 2 are greater than those of segment 1. According to Table 3, specific characteristics of the customers in each segment can be analyzed. Segment 1 (the older with middle-to-high income) demonstrates lower perceived usefulness than segment 2 (the younger with low income). Not surprisingly, the respondents in segment 2 reveal a higher perception of perceived ease of use than the older respondents in segment 1. The respondents in segment 2 are more price-sensitive than those in segment 1. The perception of hedonic motivation in segment 2 is higher than in segment 1. Lastly, the younger respondents in segment 2 demonstrate a better behavioral intention to purchase e-commerce airfares than the older respondents in segment 1.

Table 2. Descriptive Statistics for Demographic Profile.

		Segment 1		Segment 2		Total		Significance
Demographic Profile	**Measure**	*n*	%	*n*	%	*n*	%	**Chi-Square Test**
Segment Size		**1504**	**49**	**1560**	**51**	**3064**	**100**	
Age	Gen X	887	29	0	0	887	29	***
	Gen Y	617	20	1255	41	1872	61	***
	Gen Z	0	0	305	10	305	10	***
Income	Less than 25,000 Baht	288	9	1486	49	1774	58	***
	More than 25,000 Baht	1216	40	74	2	1290	42	***

Note ***: denotes significant at < 0.01; 1 Euro is approximately 36.51 Baht (source: xe.com, visit date 11 July 2022).

Table 3. Independent Sample *t*-test Results.

Psychographic Profile	Measure	Segment 1		Segment 2		Mean Diff	*t*	*t*-Test
		Mean	SD	Mean	SD			
Perceived Usefulness	PU1	3.44	0.62	3.53	0.60	0.09	−4.02	***
	PU2	3.55	0.70	3.65	0.72	0.10	−3.99	***
	PU3	3.48	0.71	3.59	0.69	0.12	−4.59	***
Perceived Ease of Use	PE1	3.14	0.77	3.32	0.76	0.18	−6.59	***
	PE2	3.23	0.94	3.48	0.80	0.25	−8.01	***
	PE3	3.20	0.95	3.50	0.81	0.30	−9.34	***
Price Sensitivity	PS1	3.13	0.90	3.40	0.82	0.26	−8.48	***
	PS2	3.20	0.89	3.35	0.85	0.15	−4.71	***
	PS3	3.19	0.93	3.42	0.86	0.23	−7.05	***
Behavioral Intention	BI1	3.10	0.94	3.28	0.85	0.18	−5.59	***
	BI2	3.21	0.96	3.36	0.90	0.15	−4.34	***
	BI3	3.37	0.90	3.51	0.79	0.14	−4.65	***

Table 3. *Cont.*

Psychographic Profile	**Measure**	**Segment 1**		**Segment 2**		**Mean Diff**	***t***	***t*-Test**
		Mean	**SD**	**Mean**	**SD**			
Hedonic Motivation	HM1	3.11	0.91	3.34	0.82	0.23	−7.26	***
	HM2	3.35	0.78	3.41	0.73	0.06	−2.15	0.032
	HM3	3.19	0.86	3.31	0.78	0.11	−3.86	***

Note: *** denotes significant at <0.01. Source: Data adapted from Authors (2021).

There are two primary steps in conducting a statistical test on SEM: the measurement model (CFA) and the structural model [82].

4.2. Step 2: Measurement Model (CFA)

The measurement model was tested utilizing CFA. The model was estimated for international consistency, reliability, convergent validity, and discriminant validity in this context. CFA was conducted by attaching all constructs with covariances [83]. All constructs must have their manifest variables before testing. Covariances among errors within the same construct could develop the GOF of the whole relationship.

4.3. The Goodness of Fit (GOF)

Table 4 illustrates the GOF measures and their thresholds. The results were acceptable since all the measures passed the recommended thresholds. The comparative fit index (CFI; 0.939), incremental fit index (IFI; 0.940), Tucker–Lewis index (TLI; 0.921), normed fit index (NFI; 0.937), goodness of fit index (GFI; 0.927) and root mean square error of approximation (RMSEA; 0.085) passed the designated thresholds.

Table 4. The Goodness of Fit of the Measurement Model.

Fit Indices	**Value**	**Threshold**	**Assessment**
p-value	≤0.001		Acceptable for complex model
CFI	0.939	>0.900	Pass
IFI	0.940	>0.900	Pass
TLI	0.921	>0.900	Pass
NFI	0.937	>0.900	Pass
GFI	0.927	>0.900	Pass
RMSEA	0.085	<0.100	Pass

Source: Data adapted from Authors (2021).

4.4. Convergent Validity

This is scrutinized by comparing the model results with the fit index thresholds. The reliability of the measurements was evaluated using Cronbach's alphas, AVE, and CR. AVE stands for average variance extracted [84], and CR stands for composite reliability [83]. According to Table 5, the recommended thresholds of the convergent validity measures and the calculated indicators are as follows.

Referring to Table 5, the price sensitivity, behavioral intention, and hedonic motivation constructs very well passed the convergent validity criteria when comparing the calculated measures with their thresholds. As for the perceived usefulness and perceived ease of use constructs, all indicators were statistically significant at the <0.001 level, but the AVEs of 0.456 and 0.439 were slightly below the thresholds (AVE > 0.50) but were still acceptable. However, the Cronbach's alphas and CR values are all above 0.7, which means that all the indicators in this measurement model passed convergent validity criteria.

Table 5. Convergent Validity.

Construct	Indicator	Loading	*p*-Value	Cronbach's Alphas (Threshold = 0.70)	AVE (Threshold = 0.50)	CR (Threshold = 0.70)
Perceived Usefulness	PU1	0.671	***	0.724	0.456	0.715
	PU2	0.72	***			
	PU3	0.632	***			
Perceived Ease of Use	PE1	0.619	***	0.705	0.439	0.7
	PE2	0.621	***			
	PE3	0.74	***			
Price Sensitivity	PS1	0.739	***	0.821	0.597	0.816
	PS2	0.735	***			
	PS3	0.84	***			
Behavioral Intention	BI1	0.818	***	0.841	0.64	0.841
	BI2	0.878	***			
	BI3	0.692	***			
Hedonic Motivation	HM1	0.812	***	0.815	0.601	0.817
	HM2	0.637	***			
	HM2	0.859	***			

Note ***: denotes significant at <0.001. Source: Data adapted from Authors (2021).

4.5. Discriminant Validity

Discriminant validity is the degree to which two or more conceptually similar constructs are different. This section is assessed by comparing the square root AVEs (on diagonal) with the associated matrices' correlations based on the Fornell and Larcker criterion [84]. According to Table 6, each AVE's square root in bold was higher than the off-diagonal correlation coefficients, indicating all the constructs could measure the different constructs theoretically, and this result was acceptable. Additionally, this study employed the heterotrait-monotrait (HTMT) ratio approach by Henseler et al. (2015) to evaluate discriminant validity, as the Fornell and Larcker (1981) criterion was criticized for its lack of reliability in addressing distinctiveness between latent variables [85,86]. The existence of discriminant validity between the related latent variables is indicated by HTMT values of more than 0.90 [85,86]. According to Table 6, the majority of HTMT values are less than 0.90, satisfying discriminant validity. However, only two pairs of latent variables (0.965 for EE and PS; and 0.973 for PE and EE) exceed the HTMT threshold. The researchers concluded that the EE, PS, and EE constructs were theoretically distinct, as evidenced by the questionnaire questions prepared following the literature review (see Appendix A). Therefore, we chose to preserve the current model and move on to the next step.

Table 6. Discriminant Validity.

	Fornell and Larcker Criterion				
	HM	BI	PS	PE	PU
HM	**0 . 775**	-	-	-	-
BI	0.466	**0 . 800**	-	-	-
PS	0.416	0.474	**0 . 773**	-	-
PE	0.307	0.350	0.330	**0 . 663**	-
PU	0.241	0.274	0.250	0.213	**0 . 675**

Table 6. *Cont.*

HTMT Ratio Approach					
HM	-	-	-	-	-
BI	0.787	-	-	-	-
PS	0.804	0.891	-	-	-
PE	0.803	0.892	0.965	-	-
PU	0.712	0.789	0.827	0.973	-

Source: Data adapted from Authors (2021). Note: HM = Hedonic Motivation, BI = Behavioral Intention, PS = Price Sensitivity, PU = Perceived Usefulness, and PE = Perceived Ease of Use.

4.6. Step 3: Structural Model

After accomplishing the prerequisite for reliability and the measurement scales' dimensionality, we continue to perform the SEM analysis. According to Figure 2 and Table 7, most of the goodness of fit criteria, as suggested by Hu and Bentler [87], supported this structural model. According to Table 8, the structural model's test results supported H2 to H4 at a significance level of 0.001 or less, which indicated that the relationships among the constructs were highly significant in statistics. The researchers establish the analysis by considering the following constructs: perceived usefulness, perceived ease of use, price sensitivity, hedonic motivation, and behavioral intention.

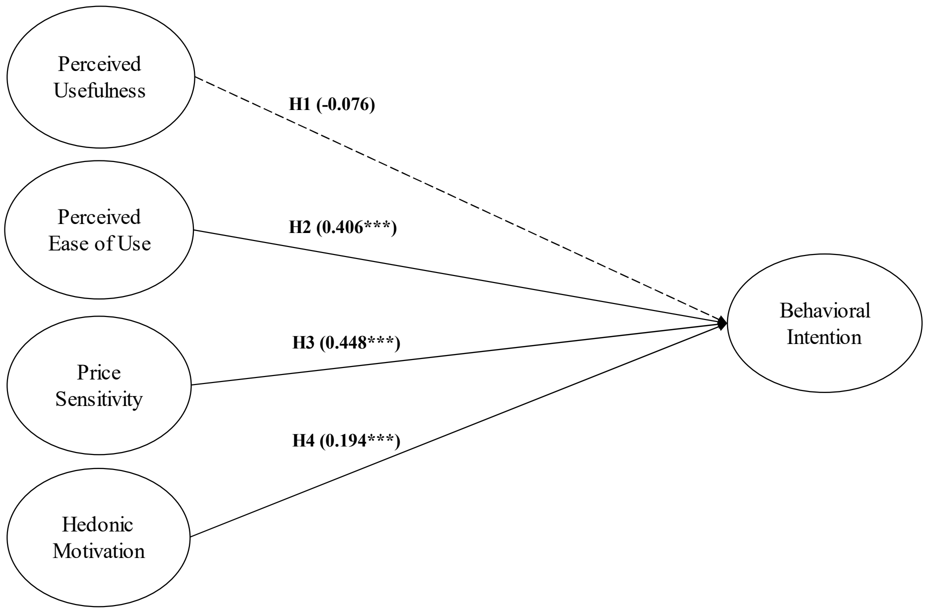

Figure 2. The Structural Model. Note: *** denotes significant at ≤0.001.

Table 7. The Goodness of Fit of the Structural Model.

Fit Indices	Value	Threshold	Assessment
p-value	≤0.001		Acceptable for complex model
CFI	0.938	>0.90	Pass
IFI	0.938	>0.90	Pass
TLI	0.919	>0.90	Pass
NFI	0.935	>0.90	Pass
GFI	0.925	>0.90	Pass
RMSEA	0.086	<0.10	Pass

Source: Data adapted from Authors (2021).

Table 8. Hypothesis Test Results from the Structural Model.

Hypothesis	Endogenous Variable	Exogenous Variable	Standardized Estimate	p-Value	Result
H1	Perceived usefulness	Behavioral intention	−0.076	0.183	Rejected
H2	Perceived ease of use	Behavioral intention	0.406	***	Supported
H3	Price sensitivity	Behavioral intention	0.448	***	Supported
H4	Hedonic motivation	Behavioral intention	0.194	***	Supported

Note ***: denotes significant at ≤0.001. Source: Data adapted from Authors (2021).

The result rejected H1, which hypothesized that perceived usefulness positively affected behavioral intention to use e-commerce airfares. Explicitly, this result demonstrated a contradictory result with a negative factor loading of −0.076, inconsistent with the technology acceptance model [12,13]. This means that passengers did not believe that the use of e-ticketing could enhance the purchasing process. They thought e-commerce airfares did not optimize their purchasing operations and allowed them to make their online booking process quicker. However, this finding is consistent with the result findings of Tahar et al. [21], which demonstrated that perceived usefulness was not a significant predictor of utilizing e-filing services. This finding could mean that in the context of the sample studied, perceived usefulness associated with the consumer buying intention of e-commerce airfares may not be an issue for them, influencing their intentions to use e-tickets. Three possible motivations could be related to this: First, it may mean that, from the perspective of respondents (Thai users) sampled, there is no conducive circumstance for them to appreciate or be unaware of improving their purchasing performance via e-commerce airfares. Second, some respondents may experience difficulty in using e-commerce in the airline industry or other industries. Third, some respondents faced internet connection issues while using e-commerce.

Furthermore, the result supported H2, which suggested that perceived ease of use positively affects behavioral intention to use e-commerce airfares with a standardized loading of 0.406. This finding is consistent with the previous study of Kumar et al. [24], who found that service convenience significantly influenced customers' behavioral intentions. This implies that passengers prefer the convenience of using online booking because of time-saving. E-ticketing provides a single operation of the online booking process. Additionally, passengers are authorized to check in online via the website and select seats available on the screen. Users feel that they can reserve airline tickets much faster than traditional counters, which motivates them to increase their intention of using e-commerce airline tickets.

Moreover, H3 was supported, which recommended that price sensitivity positively affects behavioral intention to use e-commerce airfares with a standardized loading of 0.448. This result is consistent with Escobar-Rodríguez and Carvajal-Trujillo [13], who stated that users have airline ticket online purchase intentions because of the price saving. Airline ticket purchasers tend to adopt the internet as their retail channel for airline tickets as they are more concerned about value for money and lower prices [88]. This indicated that more significant price savings would influence a greater intention to utilize the online platforms to purchase air tickets. Hence, consumers who are highly sensitive to the price of e-tickets are more likely to purchase them at the lowest price.

Moreover, H4 was supported, revealing that hedonic motivation would positively affect behavioral intention to use e-commerce airfares with a standardized loading of 0.194. This result is consistent with Tak and Panwar [40], who recommended that hedonic motivation is an essential factor in predicting the utilization of mobile applications for shopping. This means that users obtain a feeling of pleasure in utilizing e-commerce airfares via their functions and features. Thus, enjoyment of the purchasing process and engagement with the activity encourage consumers to use e-commerce for airline tickets.

4.7. Step 4: Multigroup Moderation Analysis

Measurement invariance is the method used to estimate whether respondents from two groups (segment one and segment two) interpret the same measure in a theoretically similar way [89]. The three terms of the measurement invariance approach are as follows: (1) demonstrating configural invariance, (2) demonstrating metric invariance, and (3) scalar invariance. Byrne et al. [90] indicated the difference between full and partial MI. Partial invariance is formed when only configural invariance and metric invariance are satisfied. Nevertheless, full measurement invariance is formed when partial MI and scalar invariance are accepted.

According to Table 9, even though the GFI of the scalar invariance model was slightly below the threshold of 0.90, their value (0.896) was high enough to be considered an acceptable fit [91]. The results showed that the other fit indices passed the suggested thresholds. Configural invariance, metric invariance, and scalar invariance were acceptable. Hence, the full MI was formed.

Table 9. Measurement Invariance.

Fit Indices	Configural Invariance	Metric Invariance	Scalar Invariance	Threshold
p-value	≤0.001	≤0.001	≤0.001	
CFI	0.919	0.917	0.914	>9.00
IFI	0.919	0.917	0.917	>0.90
NFI	0.914	0.912	0.908	>0.90
GFI	0.903	0.901	0.896	>0.90
RMSEA	0.070	0.069	0.067	<0.10
	Acceptable	Acceptable	Not Passed	

Source: Data adapted from Authors (2021).

Table 10 illustrates the GOF measure of the multigroup structural model and the thresholds. The results were acceptable since all the measures passed the recommended thresholds. The comparative fit index (CFI; 0.916), incremental fit index (IFI; 0.917), normed fit index (NFI; 0.912), goodness of fit index (GFI; 0.899), and root mean square error of approximation (RMSEA; 0.071) passed the designated thresholds.

Table 10. The goodness of fit of the multigroup structural model.

Fit Indices	Value	Threshold	Assessment
p-value	≤0.001		Acceptable for complex model
CFI	0.916	>0.90	Pass
IFI	0.917	>0.90	Pass
NFI	0.912	>0.90	Pass
GFI	0.899	>0.90	Acceptable
RMSEA	0.071	<0.10	Pass

Source: Data adapted from Authors (2021).

As for the path differences, considering one relationship, if the critical ratio value is less than the absolute value of 1.96, the factor loadings are insignificantly different between the two segments (see Table 11 and Figure 3). As for H1, perceived usefulness does not significantly influence behavioral intention in both segments (Segment 1′s p-value = 0.093 > 0.01 and Segment 2′s p-value = 0.852 > 0.01). This insignificant relationship implies that perceived usefulness and behavioral intention are unrelated, which represents that people in both segments do not find e-commerce airfares to improve their purchasing performance.

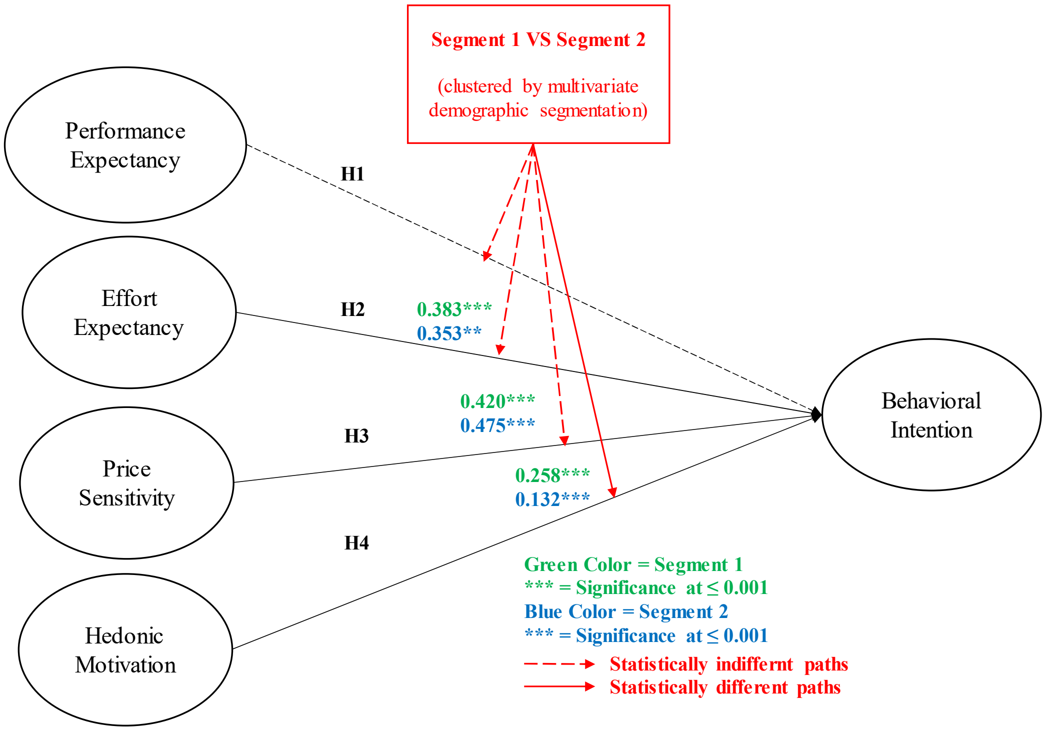

Figure 3. Segment 1 vs. Segment 2 and Final Model. Note: *** denotes significant at ≤0.001. ** denotes significant at ≤ 0.01. Source: Figure created by Authors (2021).

Table 11. Test Results for Loading Differences.

Hypothesis	Relationship			Segment 1		Segment 2		Critical Ratio Difference	Threshold
				Std. Est.	*p*-Value	Std. Est.	*p*-Value		
H1	PU	→	BI	−0.097	0.093	0.024	0.852	0.839	|1.96|
H2	PE	→	BI	0.383	***	0.353	0.001 **	−0.805	|1.96|
H3	PS	→	BI	0.420	***	0.475	***	−0.828	|1.96|
H4	HM	→	BI	0.258	***	0.132	***	−2.116 **	|1.96|

Note: *** denotes significant at ≤ 0.001, ** denotes significant at ≤ 0.01, HM = Hedonic Motivation, BI = Behavioral Intention, PS = Price Sensitivity, PE = Perceived Ease of Use, and PU = Perceived Usefulness. Source: Data adapted from Authors (2021).

However, perceived ease of use positively influences behavioral intention in segment 1 (loading = 0.383, *p*-value < 0.001) and segment 2 (loading = 0.353, *p*-value = 0.001). This indicates that consumers from both segments are concerned about website quality that delivers convenience and speed while reserving aircraft tickers. Customers can access information through the internet regarding prices, schedules, promotions, and conduct a transaction without wasting their time going to the traditional airline reservation agency. Hence, customers' decision-making on technology adoption is influenced by the ease of use while using e-commerce platforms.

Furthermore, price sensitivity positively impacts behavioral intention in segment 1 (loading = 0.420, *p*-value < 0.001) and segment 2 (loading = 0.475, *p*-value < 0.001). This indicates that both segments are likely to use e-commerce to reserve airfares due to the lower price than the traditional way. Consumers purchase e-commerce airfares because they can save money from the cheaper prices offered by online travel agencies compared to traditional channels. Airline websites also offer discounts for travelers who make online reservations. Especially, younger people will be more price-sensitive due to their low income.

Moreover, hedonic motivation positively affects behavioral intention in segment 1 (loading = 0.258, p-value < 0.001). This means that users seek experiences and enjoyment from their reservation experiences. Interestingly, hedonic motivation has a more significant impact on segment one's behavioral intention than in segment 2. This implies that segment 1′s decision-making on hedonic value is influenced more than segment 2 users. The users from segment 1 are more likely to look for the fun experience and entertainment value of using e-commerce airfares [92]. However, gen Y and Z frequently utilize other websites and social media platforms, which are more entertaining and pleasurable than the airline company's e-commerce website.

5. Discussion

5.1. Research Implications

The research results were proposed to primary stakeholders, including marketers of airline companies and online travel agencies. The findings from this research indicated that perceived ease of use highly influenced behavioral intention. A high degree of ease related to the utilization of an air ticket reservation platform enhances an individual's intention to purchase. This finding is consistent with previous research papers [23–27]. Therefore, marketers should provide a video that demonstrates the procedures for booking air tickets online. Moreover, e-commerce aircraft ticket websites or applications should be user-friendly for users. The e-commerce airfares should not be too complicated and allow consumers to take a few clicks to change to the website's next page. A website should be easy to navigate, allowing consumers to find the information they are looking for much faster.

The results suggested that price sensitivity had a substantial impact on behavioral intention to use e-commerce airfares. This result is consistent with many research articles [38–41]. Thus, marketers may offer pricing promotion activities to encourage consumers buying intention, for instance, membership schemes, frequent-buyer schemes, accumulative discount rewards, and other loyalty schemes to entice existing users to buy additional flight tickets [93].

The findings recommended that users be attracted to hedonic values by using e-commerce airfares. Hedonic motivation positively influences the purchase intention of online air tickets in Thailand, and the finding is in-line with several research articles [44–48]. Hence, marketers should design airline websites or applications to improve users' enjoyment and excitement. Marketers may attach the social networking sites with their websites or applications, which may help engage with the users. Additionally, the websites may provide music to enhance the hedonically alluring experience to make the buying experience a fun-filled exercise.

5.2. Research Limitations and Future Research

This research provides remarkable contributions to academic and business practices. However, there are a few limitations that remain in this study. The questionnaire was only sampled from people in Thailand, and the results may not cover sample groups in the surrounding countries. Future research may apply other variables of UTAUT to the current structural model, such as social influence and facility conditions, to understand consumers' behavioral intentions. Moreover, it may change the consumer segment's moderator to a more varied segment, such as educational levels and genders.

6. Conclusions

This research aims to understand how consumers use airline websites and online travel agencies to purchase airline tickets. Our findings recommend that the key factors influencing consumer behavioral intention when buying online air tickets are perceived ease of use, price sensitivity, and hedonic motivation. However, there is no significant impact of perceived usefulness on online behavioral intention, which is inconsistent with the Technology Acceptance Model. The results demonstrate that consumers have online behavioral intention due to convenience, because customers can save time by using e-commerce to reserve airline tickets. Hence, airline companies or online travel agencies should create a user-friendly website that is easy to navigate, allowing consumers to find the information they are looking for much faster. In addition, the research suggests that airline companies or online travel agencies should be aware of price sensitivity. We propose the companies offer membership schemes, frequent-buyer schemes, accumulative discount rewards, and other loyalty schemes to entice existing users to buy additional flight tickets.

In conclusion, it is recommended that airline companies and online travel agencies should consider perceived ease of use, price sensitivity, and hedonic motivation when implementing e-commerce airline websites.

Author Contributions: Conceptualization, C.P. and C.K.; methodology, P.N.; formal analysis, S.W.; resources, P.N.; data curation, S.W.; writing—original draft preparation, S.W. and S.Z.; writing—review and editing, C.P. and C.K.; supervision, C.K. and P.N.; project administration, C.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research is financially supported by Khon Kaen University International College, Thailand (No. 02F22).

Institutional Review Board Statement: Khon Kaen University Ethics Committee for Human Research, Khon Kaen University, Khon Kaen, Thailand, declared that this study met the criteria of the Exemption Determination Regulations (HE653182).

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

Data Availability Statement: Not applicable.

Acknowledgments: We would like to thank the International College and the Center for Sustainable Innovation and Society, Khon Kaen University, Thailand, for providing research facilities.

Conflicts of Interest: The authors declare no conflict of interest related to this research article.

Appendix A

Questionnaire

This research aims to understand consumer buying intention in e-commerce airfares based on demographic segmentation. You (respondent) can be confident that your personal information will be kept confidential and not shared with any third parties. This questionnaire is divided into three parts: opening questions, demographic questions, and consumer behavior questions.

Part 1: Have you ever bought an airline ticket via websites or online travel agencies?

a. Yes
b. No

Part 2: Demographic questions

(1) Gender: a. Male b. Female
(2) Generation: a. Gen X (born 1960–1979) b. Gen Y (born 1980–1994) c. Gen Z (born 1995–2010)
(3) The income per month: a. less than 25,000 baht b. more than 25,000 baht

Part 3: Consumer behavior (Answers in sub-questions are on a 1- to 5-point Likert-type scale; 1 as strongly disagree and 5 as strongly agree)

(1) Perceived usefulness
    I. I find airline company e-commerce websites or online travel agencies' websites very useful in the purchasing process.
    II. Using airline company e-commerce websites or online travel agencies' websites helps me accomplish things more quickly in the purchasing process.
    III. I can save time when I use airline company e-commerce websites or online travel agency websites in the purchasing process.

(2) Perceived ease of use
    I. The airline website or online travel agency websites are easy to use and simple to use.
    II. It is easy for me to become skillful at using airline company e-commerce websites or online travel agent websites.
    III. Using airline websites or online travel agency websites helps me purchase an airline ticket more conveniently.
(3) Price sensitivity
    I. I can save money by examining the prices of different airline companies' e-commerce websites or online travel agency websites.
    II. I like to search for cheap travel deals on different airline companies' e-commerce websites or online travel agency websites.
    III. Airline company e-commerce websites or online travel agencies' websites offer better value for my money.
(4) Hedonic motivation
    I. Using airline company e-commerce websites or online travel agencies' websites is fun.
    II. Using airline company e-commerce websites or online travel agency websites is very entertaining.
    III. Using airline company e-commerce websites or online travel agencies' websites is enjoyable.
(5) Behavioral intentions
    I. I will continue using airline e-commerce websites or online travel agency websites to purchase a ticket in the future.
    II. I am addicted to using airline company e-commerce websites or online travel agency websites.
    III. I plan to continue to use airline company e-commerce websites or online travel agency websites frequently to purchase a ticket.

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