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Improving Coverage of Travel Customer Loyalty Programs

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Abstract

To make sound decisions using customer data, travel and tourism marketers need quality information on all buyer segments. Individuals who belong to many loyalty programs may join more programs and are probably over-represented in databases. This research identifies the factors associated with widespread participation in frequent traveler and retail shopper programs with a national survey of US adults (N=1399) to identify factors associated with having more memberships. The ordered probit regression results for both types of programs were compared. Individuals with a future-focus, higher impulsivity, and more education tended to have more memberships in both program classes. Those with a today-focus, lower impulsivity, and less education tended to have fewer memberships and could be targeted with incentives to boost database coverage. Differences in results for the two types of programs suggest that loyalty membership studies need to be specific to the travel and tourism industries.

Key Words: Frequent traveler; Guest loyalty; Marketing database coverage; Impulsivity; Time preferences; Privacy concerns; Retail customers

INTRODUCTION

Around the beginning of the 21st century, firms in many industries implemented customer relationship management (CRM). These programs attempted to align business processes with customer strategies to build customer loyalty and increase profits (Rigby, Reichheld, and Schefter, 2002). Unfortunately, the general CRM failure rate was believed to be at least 40 percent (Krigsman, 2009; Johnnygrow.com, undated; Maklan, Knox, and Peppard, 2011). Consultants developed lists of the factors that contributed to these failures (e.g., Karpus-Romain, 2022). One item listed was “Employees don’t trust the data.” Academics also noted that high-quality data was essential for successful CRM and various data problems were prevalent in many implementations (e.g., Reid and Catterall, 2005). Although a specific type of CRM, loyalty programs, does not have a failure rate estimate, consultants discussed many loyalty program failures (e.g., Egeonu, 2021; Policella, 2021) and listed contributing factors (e.g., Davis, 2019). Among the items was “Failure to utilise customer data properly.” These results suggest that CRM initiatives, both general CRM and loyalty programs, may benefit from better collection and use of customer data.

Across industries, there are wide variations in loyalty program performance (Hearne et al., 2023). Some firms had difficulty making their loyalty programs profitable. A survey of marketers who used loyalty programs reported that 80.2 percent measured their program’s return on investment (ROI) (Antavo, 2023). Of the respondents who calculated their ROI, 80 percent said it was positive. In other words, 20 percent did not have a positive ROI. When the overall performances were considered, less than 60 percent of program owners said they were satisfied or very satisfied. Academics reported that some loyalty programs have had disappointing performance (e.g., Dowling and Uncles, 1997; Skogland and Siguaw, 2004; McEwen, 2005; Meyer-Waarden and Benavent, 2006; Nunes and Dreze, 2006; Lacey, 2009; Kim et al., 2009; Murthi, Steffes, and Rasheed, 2011; Lin and Bennett, 2014; Filipe, Marques, and Salgueiro, 2017). Although a travel loyalty program may not meet profitability goals, the data generated, if it covers all buyer segments and is used to improve marketing decisions, could compensate for substandard performance.

Although some programs have been cancelled, others have been created. Firms may be focusing on customer retention and trying to address the rising desire for more affective and social experiences (Liu-Thompkins et al., 2022). Consumers have signed up for the new loyalty programs. Between 2015 and 2022, the average US consumer added three loyalty program memberships (Statista, 2023). A survey in 2022 asked people about 60 different loyalty programs in 10 industries and, among those who belonged to at least one, the average number of memberships was 14 (Hearne et al., 2023).

A survey in 2023 reported that the average US consumer was a member of 18 programs (e.g., supermarket, drug store, department store, airline, hotel, car rental, gasoline station, restaurant, coffee shop, cell phone, credit cards, and "paid" programs), but was active in about half of them (Bond, 2024) [Because these surveys prompted subjects to consider various loyalty programs, there may have been "over-claiming"]. Many of these new programs may need to enhance their membership marketing so that the data is representative of their market and all buyer segments are covered.

This research attempts to learn what variables are associated with a consumer joining many loyalty programs. These individuals may be over-represented in travel program databases and may be relatively easy to attract to new loyalty programs. This analysis will also identify the variables associated with having fewer memberships, which may help firms target individuals who are less interested in loyalty programs. Two classes of programs will be considered: frequent traveler and retail shoppers. Data from a national survey will be analyzed using ordered probit regressions to learn what factors are associated with more memberships. The next section summarizes the relevant loyalty program literature and introduces the hypotheses. Then the survey is described and the results are discussed. The final section highlights the conclusions and implications from this study and describes some limitations.

LITERATURE REVIEW

Several researchers have summarized the findings from loyalty program studies. Dorotic, Bijmolt, and Verhoef (2012) concluded that programs can produce small positive changes in penetration, average purchase frequency, and average share-of-wallet (SOW). However, the effects varied by consumer segment and market. They also found that socio-demographic characteristics generally had little or no influence on enrolment. Belli et al. (2022) reviewed 110 studies and found that changes in attitudinal loyalty were necessary for long-term sales effects. However, purchase behavior changes may be larger than attitude changes. They noted that loyalty programs were less effective in industries with higher purchase frequency. This may explain why programs in some categories have had more difficulty generating profits.

A few loyalty programs have focused on current heavy users, making no effort to court light users. This can create two problems. First, today's heavy users may become lighter users in the future. Progressive program managers examine long-term profit prospects and cultivate loyalty among individuals who may become heavy users. The second problem is that light users generate a major portion of the gains from programs (Lal and Bell, 2003; Liu, 2007; Allaway, Berkowitz, and D'Souza, 2014). Many heavy users already make nearly all their purchases from one option (i.e., high SOW). Light users may patronize multiple suppliers (i.e., low SOW) before joining a program and could shift significant volume. Programs focused on heavy buyers may miss the gains from converting light users. To develop marketing programs that appeal to light users, managers need accurate information on their preferences.

Non-members have different buying patterns than members (Smith et al., 2003; Demoulin and Zidda, 2008; Meyer-Waarden, 2008; Azeem et al., 2018; Vuorinen et al., 2020). For example, Cortinas, Elorz, and Mugica (2008) found that the members of a Spanish hypermarket's program had different price sensitivities (higher in some categories and lower in others) than the average shopper. These differences were large enough to change marketing tactics. The assumption that the purchase database reflects the predilections of all prospects could generate poor marketing decisions (e.g., wrong assortment, wrong prices, etc.). Therefore, travel and tourism marketers need to broaden the participation in their loyalty programs to better assess market opportunities.

A key factor that is positively linked to the willingness to join programs is the number of loyalty cards that individuals already possess (Meyer-Waarden and Benavent, 2003; Leenheer et al., 2007; Demoulin and Zidda, 2009). Those who participate in many programs may be over-represented in a firm's customer data while those who have joined few loyalty programs are likely to be under-represented. One option to improve shopper coverage is to design special offers that appeal to people who are not members. Larson (2021) noted the coverage issues with some loyalty programs and used two direct mail surveys to develop profiles of people who joined many and few programs. The samples of Midwest adults were fielded in 2006 and 2010, before the recent surge in program memberships. The study also pooled all loyalty programs into a single category. This research will examine the memberships in frequent traveler and retail shopper programs using data from a national survey from 2022.

MEASURES AND HYPOTHESES

Individual circumstances and program features probably influence the decision to join a specific program (De Wulf et al., 2003). Customer characteristics may also predict participation in multiple programs. This section will describe the previous research and hypotheses about the people who tend to be members of many programs.

Some European studies concluded that demographic measures were probably not associated with memberships. In Sweden, age, gender, income, household size, and the presence of children were not significant (Magi, 2003). In Spain, age, gender, and household size were not significant (Lara and De Madariaga, 2007). In Belgium, age and household size were not linked to program adoption (Demoulin and Zidda, 2009).

Other studies have found links with demographics. In the Netherlands, age, income, marital status, and presence of children were associated with the number of cards owned (Van Doorn, Verhoef, and Bijmolt, 2007). In the UK, gender, presence of children, and income were linked with card ownership (Wright and Sparks, 1999). Samples from the Netherlands, New Zealand, and Australia linked gender with program attractiveness (Melnyk and Van Osselaer, 2012; Vilches-Montero et al., 2018). In the US, Larson (2021) found that income and education were associated with membership counts while gender, age, and ethnicity were not significant. These mixed results suggest that further testing of the demographics-memberships link is needed.

H1. Women are likely to have more loyalty program memberships

H2. Younger individuals are likely to have more loyalty program memberships

H3. Married individuals are likely to have more loyalty program memberships

H4. Individuals with more education are likely to have more memberships

H5. Households with children are likely to have more memberships

H6. Households with higher incomes are likely to have more memberships

Some customers may not understand how companies use loyalty program data (Graeff and Harmon, 2002). Others may be aware and have privacy concerns. Studies in the Netherlands, the US, and Spain all associated privacy concerns with loyalty programs (Leenheer et al., 2007; Ashley et al., 2011; Gomez et al., 2012). However, these studies treated privacy concerns as a single concept. Larson (2024) argued that several types of privacy concerns exist. The Smith, Milberg, and Burke (1996) scale measures multiple privacy concerns. Stewart and Segars (2002) confirmed the reliability and validity of this scale. Hinz et al. (2007) used this scale along with a technological anxiety measure in a German survey. Although they collapsed the privacy scale into a single measure, they linked both privacy concerns and technological anxiety to memberships. Larson (2021) created privacy concern factors from 8 of the 15 items in the Smith et al. (1996) scale. However, only technological anxiety was significant (and negative). These mixed findings suggest several hypotheses.

H7. Respondents with lower levels of privacy concerns are likely to have more memberships

H8. Respondents with lower levels of technological anxiety are likely to have more memberships

When people join a loyalty program, they are usually offered future rewards. While these incentives may appeal to individuals with longer-term time preferences, those with a "today focus" may be less interested. A today-focus measure, formed with a factor analysis of four questions ("The joy in my life comes from what I am doing now, not from what I will be doing later," "I try to live one day at a time," "I tend to focus on what is going on now instead of what will happen in the future," and "If I take care of the present, the future will take care of itself"), will be tested in the model.

H9. Respondents with lower today-focus scores are likely to have more memberships

When offered a membership, some consumers may join on impulse and not evaluate the benefits and costs of joining. One scale on impulsive behavior collapses into two dimensions, hedonic buying (or enjoying shopping) and impulsive traits (Hausman, 2000). Other researchers have confirmed that hedonic buying is linked to impulsiveness (e.g., Chih, Wu, and Li , 2012; Gultekin and Ozer, 2012). Enjoying shopping was an important measure for predicting program participation (Gomez, Arranz, and Cillan, 2012). Impulsiveness will be tested by the final two hypotheses.

H10. Respondents with higher hedonic buying scores are likely to have more memberships

H11. Respondents with higher impulsive trait scores are likely to have more memberships

METHODOLOGY

In July 2022, Qualtrics (www.qualtrics.com), a professional marketing research firm, was commissioned to randomly distribute an anonymous, online survey to US adults, aged 25 to 65. A total of 2676 adults started the survey. Some people did not complete the survey and two attention screens were used to improve sample quality (Abbey and Meloy, 2017). As they do for all client surveys, Qualtrics cleaned the data (e.g., dropped straight-line responses) and provided 1405 responses. Six subjects were

Table 1. Sample Profile

Demographic Measures	Sample Percentages N=1399
Female	71.7%
Non-white	44.7%
Age 35 to 44	28.5%
Age 45 to 54	21.0%
Age 55 or Higher	27.7%
Single/Separated/Widowed/Divorced	50.3%
Some College (including 2 Year Degree)	44.1%
College Graduate (4 Year Degree or More)	26.2%
Presence of Children	41.5%
Income of $40,000 to $79,999	31.5%
Income of $80,000 to $119,999	10.2%
Income of $120,000 or More	8.2%
Survey Sample Size	1399
Technological Anxiety Scale Average (Range 35 - 5)	20.08
Social Desirability Bias Scale Average (Range 16 - 0)	7.25

dropped for being outside of the target age range. The sample profile, shown in Table 1, was similar to the US population except that females were over-represented.

Subjects responded to the statements in the survey using a 7-point Likert scale (i.e., 1 was Strongly Disagree and 7 was Strongly Agree). Privacy concerns were measured with the Smith et al. (1996) scale. Many studies have used all of this scale, parts of it, or modified some questions (e.g., Milberg et al., 1995; Malhotra, Kim, and Agarwal, 2004; Schwaig et al., 2013; Hong et al., 2013). In a review of privacy concern scales, Preibusch (2013) described the Smith et al. (1996) scale as the most ‘influential’. Not all scale users identified the original four dimensions. A study of students in Taiwan found two concern factors (Lian and Lin, 2008) and a study in Canada found three factors (Campbell, 1997). Table 2 shows the privacy scale items. Scale reliability, assessed with Cronbach’s alpha and shown in Table 2, was considered very good (George and Mallery, 2003). Principle component analysis with varimax rotation identified three privacy concern factors: unauthorized use, collection, and errors.

To assess whether technology concerns influenced loyalty program participation, a five-item technological anxiety scale will be used (Parasuraman and Igbaria, 1990). Other researchers have employed this scale (e.g., Stewart and Segars, 2002; Hinz et al., 2007; Schwaig et al., 2013). The sum of five scores created the technology anxiety measure (Table 1). The average was 20.08 and the range was from 5 to 35.

The 14-item Hausman (2000) scale will be used to test for links with impulsive behavior. Other marketing studies have employed this scale (e.g., Yim et al., 2014; Larson, 2018a; 2018b; 2022; Larson and Farac, 2019). Table 3 shows the items and two factors, hedonic buying and impulsive trait, after principle component analysis and varimax rotation. One item did not fit the two-factor structure. “I go shopping to watch other people” received less agreement than in previous surveys; perhaps a structural change has occurred.

Some responses to the survey may be biased. Social desirability bias (SDB) occurs when respondents adjust their answers for impression management, self-deception, or identity definition (Larson, 2019). SDB occurs when the sample includes many subjects who change their responses and they perceive a social norm that causes them to respond in the same way. In this case, some may perceive a social norm that suggests they should have more (or less) memberships. Incorporating a SDB scale in the

Table 2. Varimax-Rotated Factor Scores for Privacy Concerns

Statements from the Smith et al.(1996) Scale	**Factor 1** Unauthorized Use	**Factor 2** Collection	**Factor 3** Errors
Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information	**0.7700**	0.1130	0.2064
When people give personal information to a company for some reason, the company should never use the information for any other reason	**0.7331**	0.1666	0.2048
Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information	**0.7225**	0.1307	0.0681
Companies should take more steps to make sure that unauthorized people cannot access personal information in their computers	**0.6833**	0.2220	0.2759
Companies should never sell the personal information in their computer databases to other companies	**0.6627**	0.2101	0.0824
Companies should devote more time and effort to preventing unauthorized access to personal information	**0.6450**	0.1492	0.2665
Computer databases that contain personal information should be protected from unauthorized access—no matter how much it costs	**0.6362**	0.1631	0.2985
It bothers me to give personal information to so many companies	0.2341	**0.8114**	0.0999
It usually bothers me when companies ask me for personal information	0.0289	**0.7690**	0.0190
I'm concerned that companies are collecting too much personal information about me	0.2332	**0.7623**	0.1455
When companies ask me for personal information, I sometimes think twice before providing it	0.3192	**0.6517**	0.2091
All the personal information in computer databases should be double-checked for accuracy -- no matter how much the cost	0.0533	0.0725	**0.7854**
Companies should take more steps to make sure that the personal information in their files is accurate	0.2252	0.0763	**0.7432**
Companies should devote more time and effort to verifying the accuracy of the personal information in their databases	0.3823	0.1645	**0.6988**
Companies should have better procedures to correct errors in personal information	0.4259	0.1794	**0.6199**
Cronbach's Alpha	0.886		

Bold indicates largest score for item.

Table 3. Varimax-Rotated Factor Scores for Impulsive Behavior

Statements from the Hausman (2000) Scale	Factor 1 Hedonic Buying	Factor 2 Impulsive Trait
Shopping satisfies my sense of curiosity.	**0.801**	0.164
I feel like I'm exploring new worlds when I shop.	**0.773**	0.132
I like to shop for the novelty of it.	**0.735**	0.287
Shopping offers new experiences.	**0.747**	0.115
I go shopping to be entertained.	**0.745**	0.248
I get a real "high" from shopping.	**0.727**	0.269
I go shopping to watch other people.	**0.296**	0.249
I often buy things without thinking.	0.132	**0.837**
"Buy now, think about it later" describes me.	0.234	**0.701**
Sometimes I'm a bit reckless about what I buy.	0.069	**0.773**
I often buy things spontaneously.	0.255	**0.759**
"Just do it" describes the way I buy things.	0.323	**0.686**
Sometimes I feel like buying things on the spur of the moment.	0.190	**0.656**
If I see something I want, I buy it.	0.362	**0.441**
Cronbach's Alpha	0.891	

Bold indicates largest score for item.

model may indicate whether many respondents perceived a norm that influenced their responses. To measure any possible impact of social expectations, the Stober (2001) scale was employed. This 16-item scale was unrelated to demographics, had good validity, and had strong internal consistency and reliability (Blake et al., 2006; Tatman and Kreamer 2014). A psychometric analysis concluded that it could be used with a Likert scale in cross-cultural settings (Tran, Stieger, and Voracek, 2012). Top-two-box [Agree or Strongly Agree] (or bottom-two-box, if reverse-scaled) responses were totaled to create a score for each subject that ranged from 0 to 16. The average was 7.25. Larson (2019) suggested using a logistic transformation so that small changes near the bottom or top of the measure's range would have less impact than changes near the middle. This measure was used to assess the impact of social expectations in the two regressions.

Two questions in the survey created the dependent measures: "How many airline/hotel/casino/travel loyalty (frequent flyer or frequent guest) programs do you participate in?" (Response options ranged from 0 to 10-or-more) and "How many supermarket/drug store/discount store/other retailer loyalty (frequent shopper) programs do you participate in?" (Response options ranged from 0 to 11-or-more). The highest response options were combined to make an 8-or-more category for each of the ordered probit regressions. Table 4 shows the response distributions.

Table 4. Dependent Variables Distributions: Number of Memberships by Type

Number of Memberships	Airline/Hotel/Casino/Travel Loyalty (Frequent Flyer or Frequent Guest) Programs	Supermarket/Drug Store/Discount Store/Other Retailer Loyalty (Frequent Shopper) Programs
0	814	261
1	226	208
2	165	328
3	90	259
4	34	147
5	22	93
6	9	28
7	12	13
8 or More	27	62
Average Memberships for People who had at Least One	2.49	3.12

RESULTS

The first columns in Table 5 show the results with all 1399 respondents for the frequent traveler regression with demographics as independent variables. The first column shows the regression results with just demographics. Non-whites, higher-educated, and higher-income individuals have more memberships while the oldest age category of respondents has fewer memberships. When the other measures are added, non-white, higher-educated, and higher-income individuals continue to have significant, positive coefficients (supporting H4 and H6). Prior studies did not report that ethnicity was important, so no hypothesis was proposed for non-whites. Some evidence suggests that the travel patterns of non-whites in the US are different (e.g., Giuliano, 2003), so they may perceive more value from travel program incentives. One privacy factor, unauthorized use, is significant and negative (partially supporting H7). Technological anxiety is not significant. Today focus is significant and negative (supporting H9). Both impulsive behavior factors are significant and positive (supporting H10 and H11). The social desirability index is significant and positive. This could suggest that frequent traveler memberships are overstated or that people who are more sensitive to social norms have joined more programs.

Travel and tourism organizations might find that their membership database contains more non-whites, higher-educated, higher-income, future-focused, and impulsive customers than expected. Individuals with more memberships also tended to have lower privacy concerns. New loyalty programs may find that non-whites, higher-educated, higher-income, future-focused, and impulsive individuals are easier to recruit. Suggesting a social expectation (e.g., everyone should join) could also boost memberships. To expand program coverage, extra communications and incentives for white, less-educated, lower-income, today-focused, and methodical shoppers along with information about privacy protections could be helpful. An advertisement could be headlined: "Planning your next vacation?" and show a family in modest surroundings looking at travel brochures. The copy might state: "Join our loyalty program now and get immediate rewards plus extra benefits when you arrive."

The results for the retail shopper regressions, shown in Table 6, are different from those for frequent traveler programs. For the demographics regression, gender, education, and presence of children have significant, positive coefficients (at the 95 percent level) and marital status (i.e., single) has a negative coefficient. When privacy concerns, technological anxiety, today focus, impulsiveness, and the social desirability index are added to the model, gender, education, and marital status remain significant (supporting H1, H3, and H4). Privacy concerns, technological anxiety, and the social desirability index are not significant. Today focus is significant and negative at the 90 percent level (some support for H9). Both hedonic buying and impulsive trait factors are significant and positive (supporting H10 and H11). This suggests that individuals who enjoy shopping and who tend to buy things on impulse also belong to more frequent shopper loyalty programs. Retailers might find that their membership database contains more women, married couples, higher-educated, future-focused, and impulsive shoppers than expected. These individuals might also be easier to attract to new programs. To expand the coverage of retail loyalty programs, extra communications and incentives for men, singles, less-educated, today-focused, and methodical (i.e., planner) shoppers could be helpful.

In the two regressions, the hypothesized relationships for age and the presence of children were not found. Gender, ethnicity, marital status, and income were only

Table 5. Ordered Probit Regression Results for Frequent Traveler Loyalty Programs

	B	Standard Error	B	Standard Error
Female	-0.005741	0.07040	-0.001667	0.07154
Non-white	0.222328**	0.06372	0.223642**	0.06605
Ages 35 to 44 Years	-0.119124	0.08662	-0.081057	0.08852
Ages 45 to 54 Years	-0.073076	0.09481	0.032835	0.09834
Ages 55 to 65 Years	-0.289716**	0.09480	-0.121658	0.10091
Single, Separated, Divorced, Widowed	-0.060330	0.06559	-0.074629	0.06645
Some College (No 4-Year Degree)	0.159271**	0.07836	0.186024**	0.08064
College Graduate (At Least 4-Year Degree)	0.311532**	0.08996	0.371878**	0.09298
Presence of Children in Household	0.093319	0.07002	0.053158	0.07098
Household Income of $40,000 to $79,999	0.339801**	0.07306	0.314847**	0.07410
Household Income of $80,000 to $119,999	0.563347**	0.10729	0.525176**	0.10914
Household Income of $120,000 or More	0.760946**	0.11718	0.701052**	0.11869
Privacy Factor: Unauthorized Use			-0.078965**	0.03318
Privacy Factor: Collection			-0.009310	0.03576
Privacy Factor: Errors			0.002966	0.03457

Technological Anxiety Score			0.004852	0.00700
Today Focus Factor			-0.077237**	0.03607
Hedonic Buying Factor			0.146203**	0.03547
Impulsive Trait Factor			0.240109**	0.03485
Social Desirability Index (Transposed)			0.235180**	0.08673
AIC Criterion		3656.49		3595.14

* Significant at 90%   ** Significant at 95%

Table 6. Ordered Probit Regression Results for Retailer Loyalty Programs

	B	Standard Error	B	Standard Error
Female	0.218642**	0.06272	0.200210**	0.06327
Non-white	0.037165	0.05652	0.031672	0.05807
Ages 35 to 44 Years	0.118999	0.07820	0.148525*	0.07926
Ages 45 to 54 Years	0.044394	0.08571	0.123556	0.08788
Ages 55 to 65 Years	-0.029488	0.08349	0.095781	0.08779
Single, Separated, Divorced, Widowed	-0.192734**	0.05816	-0.192052**	0.05849
Some College (No 4-Year Degree)	0.147491**	0.06732	0.141169**	0.06854
College Graduate (At Least 4-Year Degree)	0.285497**	0.07961	0.290465**	0.08165
Presence of Children in Household	0.124608**	0.06248	0.103304	0.06284
Household Income of $40,000 to $79,999	0.085768	0.06435	0.065213	0.06474
Household Income of $80,000 to $119,999	0.134621	0.09934	0.074805	0.10057
Household Income of $120,000 or More	0.002298	0.11048	-0.038706	0.11153
Privacy Factor: Unauthorized Use			0.039899	0.02926
Privacy Factor: Collection			0.000287	0.03138

Privacy Factor: Errors			0.017978	0.03006
Technological Anxiety Score			0.004976	0.00610
Today Focus Factor			-0.060668*	0.03158
Hedonic Buying Factor			0.172381**	0.03105
Impulsive Trait Factor			0.136667**	0.03018
Social Desirability Index (Transposed)			0.012230	0.07585
AIC Criterion		5358.58		5318.52

* Significant at 90% ** Significant at 95%

significant in one regression, highlighting the need to analyze programs by industry. The only demographic measure significant in both regressions was education (supporting H4). It was surprising that technological anxiety was not significant in either regression. Perhaps consumers have become less anxious about loyalty programs. One privacy factor was only significant in the frequent traveler regression. SDB was significant in the frequent traveler regression, but not in the retail regression, suggesting that significant SDB probably was not present. Both regressions supported H9, H10, and H11, the today-focus factor had negative coefficients and both impulsive behavior factors had positive coefficients. People with a long-term focus, who enjoy shopping, and who tend to be impulsive may be over-represented in membership databases and could also be targeted when new programs need to attract members.

CONCLUSIONS AND IMPLICATIONS

Loyalty programs, like general CRM initiatives, are difficult to successfully implement. If a marketer can attract a balanced mix of light and heavy users to their loyalty program, the data generated can help them make better decisions. Hospitality managers should not assume that their loyalty members are good reflections of their current customers or prospective customers. Previous work suggested that people with more memberships were more likely to join additional programs. This study found that individuals with more education, with a future focus, and with impulsive behaviors had more memberships in both program categories. No support was noted for relationships between memberships and age, presence of children, or technological anxiety. Gender, ethnicity, marital status, income, and privacy concerns, were significant for either travel or retail programs, but not both. By targeting individuals with the opposite traits of those who have many memberships (i.e., less educated, today-focused, methodical decision-makers, etc.), hospitality program managers can help improve loyalty program coverage. The results also demonstrate the value of examining programs by industry rather than grouping all loyalty programs together.

Like most studies, this research has some limitations. The data was from a survey sample that contained more women than expected. Self-reported memberships may undercount actual memberships because people may not recall programs that they were not actively using. Respondents who belonged to at least one of the studied program types had an average of less than six memberships, lower than the national membership estimate of about 14 in 2022 for all classes of programs. Because only two categories of programs were studied, the results may not generalize to other industries (e.g., restaurants, credit cards). Future loyalty program research should include the key variables found by this study (e.g., education, today focus, and impulsivity), consider the measures that were significant in the retail shopper regression, and test other concepts that were omitted and may be important.

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