Does the "Like" Habit of Social Networking Services Lower the Psychological Barriers to Recommendation Intention in Surveys?

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Abstract

Background: Companies often measure their customers' recommendation intention using the loyalty index based on the idea that a customer who has high loyalty and is committed to a brand has the confidence to recommend it to others. The psychological barrier is higher for recommendation intention, which may influence the behavior of others than for satisfaction on an individual level. However, the action of recommending has become commonplace due to the spread of social networking services (SNS). Pushing the "like" button for posts by family, friends, and co-workers has become an ingrained practice for consumers. Therefore, it is thought that "like" habits in SNS may lower the psychological barriers to the recommendation. **Objectives:** In this study, it was hypothesized that the more people habitually like posts on SNS, the higher the score for their recommendation intention in a customer survey. **Methods/Approach:** Propensity score matching was used to investigate a causal effect between the likes and the recommendation intention in a customer survey. **Results:** Based on the results of an online survey of chocolate brands in Japan, the causal effect was verified by propensity score matching. **Conclusions:** The results suggest that not only in companies but also in academic research, a valid concern is that the causal effect cannot be accurately evaluated unless a survey design is performed in consideration of the effects.

Keywords: customer relationship management; loyalty; customer survey; social networking services

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Introduction

Customer relationship management (CRM) is a corporate activity that has long been emphasized as important. Its purpose is to build long-term loyalty and increase profits efficiently (Rigby et al., 2002). In other words, increasing loyalty contributes significantly to company profits. Two main factors influence loyalty to profits. One is the increase in the repurchase rate. It is said that the retention of existing customers as repeaters is several times more efficient than acquiring new customers (Reichheld and Sasser, 1990). The other is for customers to act as "sales personnel" and recommend brands to their acquaintances. Loyal customers are passionate about the brand, understand the product well, and act as evangelists for the brand (Aaker and Joachimsthaler, 2000).

Therefore, managing customer loyalty in CRM is extremely important for companies. Typical indicators used in marketing research to measure loyalty are repurchase intention and recommendation intention. Repurchase intention is frequently used as a loyalty index. However, for durable consumer goods with a long replacement period, it is difficult for consumers to indicate this intention unless they are aware of the next purchase (Kato, 2019). On the other hand, recommendation intention can be indicated without being affected by the length of the replacement period. Customers with high loyalty and commitment to the brand are confident enough to recommend it to others (Aaker, 1991). This means that the psychological barrier to recommendation intention to influence the behavior of others is higher than that to satisfaction through individual emotions. Beyond that barrier, having a recommendation intention is a strong indication of interest in the brand. Based on this idea, recommendation intentions have been generally used in marketing surveys that measure loyalty in both industry and research.

However, recommending has become common due to the spread of social networking services (SNS). Consumers are in the habit of pushing the "like" button for posts by the people they follow. Although it is thought that like habits in SNS may lower the psychological barriers to the recommendation in a customer survey, few examples quantitatively show this effect. Accordingly, the purpose of this study is to clarify the effect of like habit in SNS to reduce the psychological barrier of favorable reaction of recommendation intention in marketing research. An online survey was conducted on Japanese chocolate brands, and the effect was evaluated by propensity score matching. This study provides implications for the design of customer surveys that are regularly conducted in business.

The literature review section describes previous research on the penetration status of SNS and like motive. The methodology section describes the survey and data analysis methods. Then, the results and discussion section describe the results and implications for practice. Finally, the conclusion section describes the summary, limitations, and future research tasks.

Penetration status of SNS and like motive

Currently, 511,200 tweets are posted every minute on Twitter worldwide, 55,140 photos are posted on Instagram every minute (Domo, 2019), and Facebook posts are liked more than 3 billion times a day (Moffat, 2019). In this way, SNS is rooted in the daily life of consumers. In the United States, 86% of people use social media at least once a day (Herhold, 2018), and Facebook, which is the most used SNS, is used by about 70% of people (Perrin and Anderson, 2019). The most used SNS in Japan is Line, which is used by 82% of people (Mori and Nitto, 2020). It should be noted that Line is a means of contact in a closed community with family and friends, so its purpose is different from Facebook, Twitter, and Instagram, which are used to share information widely and publicly. Therefore, Line was excluded from this study.

"Likes" on SNS were first introduced by the video site Vimeo in 2005 but have spread globally, being adopted by Facebook in 2009 (Moffat, 2019). When Facebook was first developed, it was considered an "awesome" button instead of "like." However, there was concern that users would find the button annoying (Khrais, 2018). Ultimately, the function to show support for family members and friends easily and make recommendations to others has resulted in an environment that encourages consumers to post.

Likes have a substantial impact on business, so companies attach great importance to them (Lipsman et al., 2012; Trattner and Kappe, 2013). The like button was installed within a few months of Facebook's appearance on more than 350,000 websites, including BestBuy.com (Gelles, 2010). A 1% increase in the number of likes of pre-released movies was shown to increase box office revenue in the first week by about 0.2% (Ding et al., 2017). Accumulated likes are also used in academic studies because they are sources of information that express user preferences. Like data show that detailed personal attributes such as ethnicity and political views can be inferred (Kosinski et al., 2013; Youyou et al., 2015).

As mentioned above, likes can recommend content to family members and acquaintances with one click. However, likes' motives are not so simple. They are used for various purposes including maintaining social ties with acquaintances and making dating efforts (Chin et al., 2015; Eranti and Lonkila, 2015). Hence, consumers may have a habit of blindly pushing the like button regardless of whether the content is good. As a result, research has focused on the possibility that SNS reduces the psychological barrier to the act of recommendation. Thus, in this study, it was hypothesized that "the more people that habitually press like on SNS, the higher the score for their recommendation intention in a customer survey." There are few examples of scientifically verifying this hypothesis.

Methodology

Method of survey

In this study, an online survey was conducted in Japan from May 22 to 26, 2020. Chocolate was set as the target product because it was considered a product that people would easily recommend to others. For example, items like health insurance, which is associated with sensitive information such as medical history, and luxury watches, for which people often have strong preferences, would be inappropriate for this study. Four major chocolate product brands in Japan were chosen. All brands are by different manufacturers. There are two conditions for the respondents: they should (a) be aged 20 to 60, and (b) have a habit of purchasing chocolate at least once a week. The sample size was set at 5 generations x 2 genders = 10 categories, with a total of 1,000 people, with 100 in each category. The survey was distributed by email until the target sample size was achieved. The number of emails sent was 72,743, the number of participants was 9,012, the number of respondents who answered completely was 7,134, and the number of those who met the respondent conditions was 1,325. Then, the sample of 1,000 people was randomly selected so that generation and gender were even. This sample was used for verification.

The online survey method has been criticized for a minimization of efforts called "satisficing" that reduces the reliability of answers (Krosnick, 1991). Therefore, reducing the number of questions in the survey is effective in increasing reliability and lessening the burden on the respondents. Based on this, the following 10 items were asked about: (1) gender, (2) age, (3) living area, (4) annual household income, (5) frequency of SNS usage (Facebook, Twitter, Instagram, TikTok), (6) average monthly frequency of likes on others' posts via the four SNS, (7) average monthly frequency of posting on the four SNS, (8) frequency of chocolate purchase, (9) most purchased brands (four brands were presented as options), and (10) recommendation intention for the most purchased brand.

The target of this study is the relationship between likes and recommendation intention, but the relationship between posting and recommendation intention was also confirmed. It is ideal to use the data tracking usage status to accurately grasp the frequency of likes and posts on SNS. However, this method has a high risk of privacy infringement. Therefore, in (6) and (7), the method of asking participants to share the average number of times they used the like function or posted per month was selected. Considering how limited memory can be, it was difficult for consumers to answer the number of likes individually for each SNS. Therefore, the total number of likes given in the four chosen SNS (Facebook, Twitter, Instagram, and TikTok) were collected.

As shown in Table 1, the SNS with the highest usage rate is Twitter (60.4%), followed by Facebook (53.9%), Instagram (52.3%), and TikTok (28.2%).

Table 1
Frequency of SNS usage

Frequency of use	Facebook		Twitter		Instagram		TikTok		Total	
	Freq	Ratio	Freq	Ratio	Freq	Ratio	Freq	Ratio	Freq	Ratio
Every day	237	23.7%	337	33.7%	281	28.1%	118	11.8%	973	24.3%
Four to six times a week	81	8.1%	83	8.3%	78	7.8%	68	6.8%	310	7.8%
Two to three times a week	81	8.1%	90	9.0%	85	8.5%	47	4.7%	303	7.6%
Less than once a week	140	14.0%	94	9.4%	79	7.9%	49	4.9%	362	9.1%
Never use	461	46.1%	396	39.6%	477	47.7%	718	71.8%	2,052	51.3%
Total	1,000	100.0%	1,000	100.0%	1,000	100.0%	1,000	100.0%	4,000	100.0%
Utilization ratio	–	53.9%	–	60.4%	–	52.3%	–	28.2%	–	48.7%

Source: Authors' work

As shown in Table 2, the usage rate of Twitter by generation shows that the usage rate is higher among younger participants.

Table 2
Frequency of Twitter usage by generation

Frequency of use	The 20s		The 30s		The 40s		The 50s		The 60s	
	Freq	Ratio	Freq	Ratio	Freq	Ratio	Freq	Ratio	Freq	Ratio
Every day	122	61.0%	86	43.0%	67	33.5%	41	20.5%	21	10.5%
Four to six times a week	28	14.0%	18	9.0%	10	5.0%	15	7.5%	12	6.0%
Two to three times a week	9	4.5%	22	11.0%	28	14.0%	17	8.5%	14	7.0%
Less than once a week	12	6.0%	16	8.0%	19	9.5%	25	12.5%	22	11.0%
Never use	29	14.5%	58	29.0%	76	38.0%	102	51.0%	131	65.5%
Total	200	100.0%	200	100.0%	200	100.0%	200	100.0%	200	100.0%
Utilization ratio	–	85.5%	–	71.0%	–	62.0%	–	49.0%	–	34.5%

Source: Authors' work

Table 3 shows that the average number of likes per month is 10.33 It is noteworthy that 452 respondents out of 1,000 selected 0 times. For posting, the mean is 3.62 times, which is smaller than the likes, and the number of respondents who answered 0 times reached 556, which is the majority. These people are referred to as "read-only members (ROM)."

Here, it is necessary to define groups based on "liking and posting" frequency. Based on the observed distribution, Group 1 is defined as 0 times (ROM), Group 2 as 1–5 times, Group 3 as 6–30 times, and Group 4 as 31 times or more and who like posts once or more every day. Thus, it was verified that the tendency of responding to the recommendation intention was significantly higher in the treatment groups, Group 2–4 (people who have liking/posting habits), than in the control group, Group 1 (people who do not have liking/posting habits).

The recommendation intention in (10) was: "How much would you recommend the brand that you selected as your most purchased to friends and acquaintances?" The answer options ranged from "1: Not recommend at all" to "10: Highly recommend." The mean value was 7.097 and the standard deviation was 1.751.

Table 3

Likes and Posts per month on SNS

	Descriptive statistics				Group				Total
	Mean	Median	Min	Max	Group 1 (0)	Group 2 (1-5)	Group 3 (6-30)	Group 4 (31-)	
Like	10.326	1	0	500	452	285	196	67	1000
Post	3.62	0	0	200	556	317	105	22	1000

Source: Authors' work

Method of verification

When the random assignment is possible, it is appropriate to perform the most reliable method of randomized controlled trial on a scientific basis (Torgerson and Torgerson, 2008). However, it is difficult to instruct a randomly selected person to communicate a certain period of their performance by specifying the frequency of likes on SNS. In addition, it is more appropriate, for this study, to gain information about a habit rather than forcibly encouraging participants to press the like button.

A propensity score proposed by Rosenbaum and Rubin (1983) is a typical method for estimating the causal effect when random assignment is difficult. Covariates are adjusted by aggregating multiple covariates into one variable called the propensity score. The characteristics of consumers tend to be biased between those who have a large number of likes on SNS and those who do not. Therefore, the causal effect is estimated by matching respondents with close propensity scores to each other and homogenizing both groups.

Since the true value of the propensity score of each respondent is unknown, it is common to estimate it from the data using a logistic regression model. As shown in Table 4, the acquired attribute variables were made into dummy variables and put into the explanatory variables of the model. The dummy variable criterion is not used in the model. The objective variable was 0/1, indicating either the control group or the treatment group. That is, the propensity score represents the probability that each respondent belongs to the treatment group. Since there are many explanatory variables, the stepwise method was used to select variables. In this study, since multiple comparisons were performed, the propensity score was estimated for each of the two target groups: for likes, Group 1 vs. Group 2 (Test 1), vs. Group 3 (Test 2), vs. Group 4 (Test 3), and for posts, vs. Group 2' (Test 1'), vs. Group 3' (Test 2'), vs. Group 4' (Test 3').

Table 4
Attribute variable used for propensity score matching

No	Variable	Breakdown	Mean	SD
	Gender			
1	Female	Female	0.500	0.500
	Age			
2	Age_20s	20s	0.200	0.400
3	Age_30s	30s	0.200	0.400
4	Age_40s	40s	0.200	0.400
5	Age_50s	50s	0.200	0.400
6	Age_60s	60s	0.200	0.400
	Residential area			
7	Area_01_Hokkaido	Hokkaido	0.043	0.203
8	Area_02_Tohoku	Tohoku	0.101	0.301
9	Area_03_Kanto	Kanto	0.458	0.498
10	Area_04_Tokai	Chubu	0.100	0.300
11	Area_05_Kinki	Kansai	0.143	0.350
12	Area_06_Chugoku	Chugoku	0.041	0.198
13	Area_07_Shikoku	Shikoku	0.019	0.137
14	Area_08_Kyusyu	Kyusyu	0.095	0.293
	Household income			
15	Income_199	Less than two million yen	0.073	0.260
16	Income_200_399	Two to four million yen	0.214	0.410
17	Income_400_599	Four to six million yen	0.223	0.416
18	Income_600_799	Six to eight million yen	0.181	0.385
19	Income_800_999	Eight to 10 million yen	0.126	0.332
20	Income_1000_1499	10 million to 15 million yen	0.117	0.322
21	Income_1500	15 million yen or more	0.066	0.248
	Most purchased brand			
22	Brand_A	Brand A	0.331	0.344
23	Brand_B	Brand B	0.257	0.232
24	Brand_C	Brand C	0.142	0.349
25	Brand_D	Brand D	0.270	0.255

Source: Authors' work

The difference in the distribution of recommendation intention was verified by Fisher's exact test for the two groups matched using the propensity score. The reason the chi-square test was not applied is that there are numbers less than 10 in the cell. The null hypothesis is that "there is no difference in the distribution of recommendation intention between the two groups." The null hypothesis is rejected and a significant difference is confirmed when the p-value becomes smaller than 0.05.

To ensure that the test is rigorous, the following two procedures were performed. First (see Table 5), the recommendation intention was converted from 10 levels to 4 levels; Low: 1–2, Lower-middle: 3–5, Upper-middle: 6–8, and High: 9–10. This is because if the distribution is made finer than necessary, even slight differences that have essentially no meaning are detected. Second, the sample size was adjusted appropriately. A sample size that is too large will detect even meaningless differences. Therefore, the appropriate sample size was confirmed by power analysis. It was calculated that 121.13 by significance level was 5%, the power of the test was 80%, the effect size was medium at 0.3 (Cohen, 1992), and the degree of freedom was 3. Therefore, 60 people in each group, 120 people in total, were randomly sampled for each test.

Table 5
Distribution of recommendation intentions

Recommendation intention	Number of people
Low (1-2)	13
Lower-middle (3-5)	164
Upper-middle (6-8)	626
High (9-10)	197
Total	1000

Source: Authors' work

Statistical analysis software R was used. The stepwise method was the stepAIC function of the MASS package, the propensity score matching was done using the Match function of the Matching package, and the power analysis was conducted through the pwr.chisq.test function of the pwr package.

Results and discussion

First, the propensity score was calculated by the logistic regression model. Table 6 shows the results of Test 1–Test 3 for likes. The odds ratio of Age_40s, Age_50s, and Age_60s was well below 1 in all models. This means that if consumers are in their 40s or older, fewer people commonly press the like button. From the SNS usage rate according to age in Table 2, it can be seen that the relationship between SNS and age is strong. The validity of the model was confirmed because the c-statistics were 0.7 or more in all models. The same was done for Test 1'–Test 3' for posts.

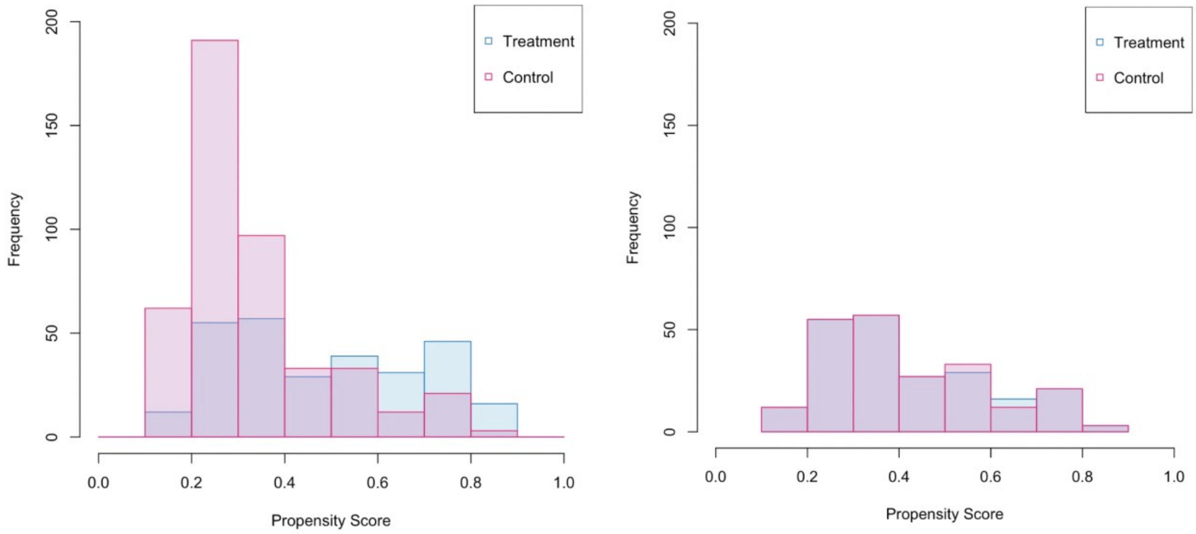
Table 6
Estimated result of logistic regression model

Variable	Test1 (Group 1 vs Group 2)				Test1 (Group 1 vs Group 3)				Test3 (Group 1 vs Group 4)			
	Odds ratio	SE	p-value		Odds ratio	SE	p-value		Odds ratio	SE	p-value	
(Intercept)	2.822	0.234	0.000	***	2.884	0.247	0.000	***	0.399	0.197	0.000	***
Female	0.578	0.165	0.001	**	0.628	0.190	0.014	*				
Age_30s	0.460	0.274	0.005	**	0.307	0.299	0.000	***				
Age_40s	0.232	0.277	0.000	***	0.241	0.286	0.000	***	0.227	0.378	0.000	***
Age_50s	0.110	0.288	0.000	***	0.096	0.307	0.000	***	0.138	0.399	0.000	***
Age_60s	0.172	0.272	0.000	***	0.066	0.336	0.000	***	0.049	0.617	0.000	***
Area_01_Hokkaido					0.190	0.804	0.039	*				
Area_02_Tohoku					0.463	0.353	0.029	*				
Income_1000_1499									1.921	0.388	0.092	
Income_1500									3.529	0.475	0.008	**
c-statistics		0.723				0.755				0.785		

Note: ***p<0.001; **p<0.01; *p<0.05. SE: standard error
Source: Authors' work

Using the estimated propensity score, the control group and the treatment group were homogenized. As shown on the left side of Figure 1, the distribution of propensity scores of Test 1 can be understood to be completely different. As a result of propensity score matching, 224 respondents were extracted from each group, and as shown on the right side of Figure 1, the propensity scores are homogenized. As shown in Table 7, even when compared for each variable, the values are almost the same. Similarly, 163 respondents in each group were extracted in Test 2, 64 respondents in Test 3, 273 respondents in Test 1', and 105 respondents in Test 2'. However, Test 3' was excluded from verification because the test only had 21 respondents, below the standard of 60 participants. As shown in Table 3, the reason for this is that posting is less frequent than liking.

Figure 1
Distribution of propensity scores for Test 1(left: before matching, right: after matching)



Source: Authors' work

Table 7
Results of propensity score matching

Variable	Test1			Test2			Test3		
	Group 1	Group 2	SMD	Group 1	Group 3	SMD	Group 1	Group 4	SMD
Female	0.433	0.433	0.000	0.436	0.454	0.037	0.578	0.531	0.094
Age_30s	0.263	0.263	0.000	0.270	0.252	0.042	0.406	0.328	0.161
Age_40s	0.219	0.219	0.000	0.258	0.258	0.000	0.172	0.172	0.000
Age_50s	0.152	0.152	0.000	0.166	0.166	0.000	0.141	0.141	0.000
Age_60s	0.219	0.219	0.000	0.110	0.110	0.000	0.047	0.047	0.000
Area_01_Hokkaido	0.040	0.094	0.215	0.012	0.012	0.000	0.000	0.000	0.000
Area_02_Tohoku	0.125	0.112	0.041	0.055	0.074	0.075	0.125	0.094	0.099
Area_04_Tokai	0.125	0.103	0.070	0.117	0.061	0.194	0.141	0.109	0.094
Area_05_Kinki	0.134	0.138	0.013	0.110	0.147	0.110	0.141	0.203	0.165
Area_06_Chugoku	0.022	0.067	0.217	0.018	0.037	0.112	0.031	0.031	0.000
Area_07_Shikoku	0.000	0.022	0.213	0.006	0.061	0.308	0.000	0.000	0.000
Area_08_Kyusyu	0.103	0.080	0.077	0.153	0.086	0.208	0.109	0.078	0.107
Income_200_399	0.228	0.183	0.110	0.184	0.147	0.099	0.188	0.203	0.039
Income_400_599	0.228	0.250	0.052	0.270	0.233	0.085	0.203	0.156	0.121
Income_600_799	0.165	0.165	0.000	0.141	0.215	0.193	0.078	0.219	0.400
Income_800_999	0.156	0.138	0.050	0.129	0.129	0.000	0.109	0.094	0.051
Income_1000_1499	0.116	0.116	0.000	0.135	0.092	0.135	0.188	0.188	0.000
Income_1500	0.058	0.067	0.037	0.074	0.080	0.023	0.094	0.094	0.000
Brand_B	0.041	0.009	0.204	0.043	0.074	0.131	0.047	0.063	0.068
Brand_C	0.136	0.177	0.112	0.135	0.160	0.069	0.156	0.172	0.042
Brand_D	0.059	0.036	0.107	0.049	0.080	0.125	0.063	0.063	0.000
Sample size	224	224	–	163	163	–	64	64	–

Source: Authors' work

As shown in Table 8, as a result of applying Fisher's exact test in Test 1 (p-value=0.270), the null hypothesis was not rejected. However, in Tests 2 and 3, the p-value was smaller than 0.05, and a significant difference was confirmed. Cramer's V represents the effect size and is generally judged as 0.1=small, 0.3=medium, and

0.5=large (Khalilzadeh and Tasci, 2017; Grant et al., 2012). Since both Tests 2 and 3 are 0.3 or more, the effect size is medium. Next, looking at the post results shown in Table 9, as with the likes, there was no significant difference in Test 1′, but in Test 2′, a significant difference in effect size similar to that for likes was confirmed.

Table 8

The effect of the frequency of Likes on the response to recommendation intention

Test	Like	Recommendation intention				Total	p-value	Cramer's Va
		Low	Lower-middle	Upper-middle	High			
1	Group 1	1	16	35	8	60	0.270	0.177
	Group 2	0	12	33	15	60		
2	Group 1	2	14	40	4	60	0.008**	0.302
	Group 3	1	5	39	15	60		
3	Group 1	0	11	45	4	60	0.001***	0.335
	Group 4	0	9	31	20	60		

Note: ***p<0.001; **p<0.01; *p<0.05. a effect size 0.1=small, 0.3=medium, 0.5=large
Source: Authors' work

Table 9

The effect of the frequency of Posts on the response to recommendation intention

Test	Post	Recommendation intention				Total	p-value	Cramer's Va
		Low	Lower-middle	Upper-middle	High			
1'	Group 1	1	10	41	8	60	0.166	0.196
	Group 2	0	13	32	15	60		
2'	Group 1	2	17	33	8	60	0.000***	0.407
	Group 3	0	2	37	21	60		

Note: ***p<0.001; **p<0.01; *p<0.05. a effect size 0.1=small, 0.3=medium, 0.5=large
Source: Authors' work
large

From the above, the hypothesis "the more people that habitually press like on SNS, the higher the score for their recommendation intention in a customer survey" was supported. As expected, consumers with stronger like habits are more likely to have lower psychological barriers to responding positively to the survey's recommendation intention. In addition, the conditions under which this effect occurred were also clarified. Here, there was no significant difference in the group with a mean monthly rate of 1–5 times compared to those who do not use the like function. Similar results were obtained for posts. This is an expected result because there is a correlation between liking and posting. The correlation coefficient based on the data of 1,000 people was 0.686, and the result of Pearson's product-moment correlation was p-value=0.000, confirming a correlation between both variables.

One of the most important features in a regular customer survey in a company is to survey the same item at the same time for the same sample. However, since it is difficult to continue surveying the same individuals, a homogeneous sample is extracted each time. If there are variations in these values, biases will affect the data, and it will not be possible to obtain true values. Therefore, in companies, this is managed as a matter of course. However, the conditions of the survey respondents are often limited regarding age, gender, and residential area. There are few cases where the usage status of SNS is included. If the usage status of SNS is different for each survey sample, there is a concern that the recommendation intention increases due to the effects of SNS habits rather than because of products and services. As technology progresses rapidly and the usage of SNS changes from moment to moment, this should be taken into consideration when designing a survey.

Conclusion

In managing loyalty, companies regularly measure recommendation intention. Customers with high loyalty and commitment to the brand are confident enough to recommend it to others. In other words, the psychological barrier is higher for recommendation intention, which may influence the behavior of others, than for emotions of satisfaction experienced by the individual. However, the action of recommendation has become commonplace due to the popularity of SNS. It has become a daily practice for consumers to like posts by family members and acquaintances. Therefore, it was thought that like habits in SNS may lower the psychological barrier of recommendation intention.

Thus, in this study, the hypothesis that "the more people that habitually like posts on SNS, the higher their score for recommendation intention in a customer survey" was verified by using propensity score matching for the data observed in the online survey. As a result, a significant difference was confirmed between the group that does not habitually "like" posts and the group that does. Thus, the hypothesis was supported for chocolate brands in Japan. According to Cramer's V criteria, the effect size is medium. Further, it is considered undesirable to ignore this effect. However, it was also revealed that there was no significant difference between those who used the like function on average 1–5 times monthly compared to those who did not use like at all.

In a company's CRM activities, the results of regular customer surveys are used as material for decision-making. At that time, if the respondents' usage of SNS fluctuates, the result may be biased, and there is a concern that decision-making may be mistaken. Since the recommendation intention is frequently used in academic research as well, it may be necessary to consider this effect for precise verification.

A limitation of this study is that the number of likes/posts used in the data is based on a self-reported attitude survey rather than recorded behavior. If a behavioral record could be used without violating the participants' privacy, not only could detailed conditions of the effect occurrence be understood, but the effect of each SNS could be verified. In addition, this study did not consider the motives for likes. By considering motives in addition to the number of times, it may be possible to understand the conditions that influence the response of the recommendation intention. This is something that should be investigated in future studies.

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