

# Customer segment transition through the customer loyalty program

Customer segment transition

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Received 3 September 2020  
Revised 29 December 2020  
6 February 2021  
9 April 2021  
Accepted 4 May 2021

## Abstract

**Purpose** – This study presents the applicability of a model-based approach for loyalty program forecasting using smartphone app in the digital strategy of the retail industry.

**Design/methodology/approach** – The authors develop a dynamic model with the cyclical structure of customer segments through customer experience. They use time-series data on the number of members of the loyalty program, “Seven Mile Program” and confirm the validity of the approximate calculation of customer segment share, customer segment sales share and aggregate sales performance. The authors present three medium-term forecast scenarios after the launch of a smartphone payment service linked with the loyalty program.

**Findings** – The sum of the two customer segment shares for forecasting (the sum of the quasi-excellent and excellent customer ratios) is about 30% in each scenario, consistent with an essential customer loyalty (true loyalty) share obtained in the existing empirical study.

**Research limitations/implications** – Digital strategy in the retail industry should focus more on estimating and forecasting average amounts of customer segments and the number of aggregated customers through the digitalization on the customer side than on individual customer journeys and responses.

**Practical implications** – Multi-scenario evaluation through simulation of dynamic models from a systemic view can be used for decision-making in retailing digital strategies.

**Originality/value** – This study builds a model that integrates the cyclicity of customer segment transition through customer experiences into a loyalty matrix framework, which is a method that has previously been used in the hospitality industry.

**Keywords** Customer journey, Customer loyalty, Smartphone app, Digital strategy, Forecasting, System dynamics

**Paper type** Research paper

## Introduction

The conceptualization of the customer journey during the pre-purchase, purchase and post-purchase stages has been shown based on the theory of market or business strategy (Handarkho, 2020; Lemon and Verhoef, 2016; Grewal and Roggeveen, 2020). Recent empirical studies have focused on touchpoints across multichannel or omnichannel retailing, and large-scale data analysis based on the static models of the customer journey have provided implications for customer segments and customer experience management (de Haan *et al.*, 2018; Chen *et al.*, 2019; Handarkho, 2020; Jo *et al.*, 2020). However, the existing empirical research models rarely consider the transitions between customer segments and the performance forecast by all customers in the customer journey. This study traces how the customer segment size (cumulative sum), based on the customer loyalty classification,



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*Funding:* This work was supported by JSPS KAKENHI Grant Numbers JP17K04017, JP19H01534.

Asia Pacific Journal of Marketing  
and Logistics  
Vol. 34 No. 3, 2022  
pp. 611-626  
Emerald Publishing Limited  
1355-5855  
DOI 10.1108/APJML-09-2020-0630

changes over time. It proposes a dynamic model that captures the whole loop structure and non-linearity of performance (Grewal and Roggeveen, 2020) from a systemic view rather than individual customer journeys. “A systematic view” means that this study does not focus on tracking the path of each customer over multiple touchpoints, as described in previous literature, but is focused on approximate calculations of population migration (time transitions) and aggregated purchase amounts that take into account the circulation between customer loyalty segmentation through multiple types of customer experiences.

Using a single case analysis, we select a loyalty program (“Seven Mile Program”) launched by Seven and i Holdings (2019a), the largest retailer in Japan, in 2018 as a smartphone app for customers of the physical stores. Through the approximate calculation of the number of Seven Mile Program members and the overall business performance using the published data, we attempt to estimate the purchase amounts by customer segment and further forecast the performance as the business scenarios.

Digital strategy refers to a business and/or corporate strategy that focus on digitalization. The essence of digital strategy requires consideration of the transition from quantitative change to qualitative change (understood as digital transformation) as a competitive advantage through three types of core digitalization processes: expression, connectivity and aggregation. Digital transformation from a business perspective includes shifting from a focus on responding to customer demand, choices and preferences to a focus on forecasting (Adner *et al.*, 2019). Consumers constantly use smartphones in daily life and can update the combination of services used and their current circumstances. One of the retailers’ digital strategies is adopting a loyalty program using a smartphone app. The diffusion of loyalty programs by smartphone apps in the retail business may transform the customer experience in all stages, change the customer journey (de Haan *et al.*, 2018; Handarkho, 2020) and result in profound customer engagement (Pansari and Kumar, 2017).

This study refers to a loyalty program (“Seven Mile Program”) across the retail group companies of Seven and i Holdings (Seven and i) as the single case of the digital strategy in the retail industry. Seven and i is a pure holding company of group companies, including convenience stores, superstores, department stores, supermarkets and financial services in Japan.

Seven and i realized the unification of customer identifications for the group companies and called it 7iD. Since June 2018, the Seven Mile Program, a loyalty program for group companies, has been in full operation. This loyalty program allows its users to log in to the iOS and Android smartphone apps provided by each group company using 7iD, enabling a unified view of customer purchase information across group companies and stores. Thus, the 7iD-based data integration platform made it possible to conduct customer analysis across the group companies (Ryutsuu News, 2018a, b).

### Related prior research

#### *Customer journey and customer engagement (CE)*

Lemon and Verhoef (2016) describe the customer journey as all processes that a customer goes through across all stages (pre-purchase, purchase and post-purchase stages) and touchpoints that make up the customer experience. They also indicate that the overall approach to modeling the customer journey has two options: an aggregated sales model and an individual behavior attribute model. Previous empirical research mainly focused on the customer journey models (CJMs) using online behavior records and e-commerce data and argued for the interdependence between multiple channels and customer behaviors (Chen *et al.*, 2019; Handarkho, 2020).

In the marketing field, CE is a common term meaning “customer activity that targets a company.” According to Pansari and Kumar (2017, p. 295), CE is defined as “the mechanics of a customer’s value addition to the firm, either through direct or/and indirect contribution.”

van Heerde *et al.* (2019) conducted an empirical study of retail mobile apps and CE. They developed the purchase model (a probit model) for each customer based on the access records and purchase data and estimated the annual revenue amount assuming an average transaction value of US\$100 per customer and a total sales amount for 100,000 people.

### *Customer loyalty and the loyalty program*

More recently, retailers have adopted customer loyalty programs that have long been used by the travel, hospitality and leisure industries. Customer loyalty is one critical key to retail business success, and retaining an existing customer costs far less than acquiring new ones. One way to do this is to create customer loyalty programs that effectively reward the best—or potentially important—customers. Further, these program participants will spend more than the non-participants (Gable *et al.*, 2008).

Customer loyalty has a complex multidimensional structure involving behavioral (repeat purchases) and attitudinal components (Dick and Basu, 1994; Bowen and Shoemaker, 1998). Bowen and Shoemaker (1998) claim that loyalty is the likelihood of a customer returning and their willingness to behave as a partner to the organization. Loyalty programs are designed to cultivate customer loyalty by rewarding repeat purchases. Members of a loyalty program reap a wide variety of “hard” benefits (e.g. discounts, coupons and rebates for past purchases) and “soft” benefits (e.g. special invitations, shopping convenience, and therefore are likely to become dedicated patrons of a store (Gable *et al.*, 2008; Pan *et al.*, 2012)). Customer loyalty program membership tends to enhance customer loyalty (Tanford and Baloglu, 2012). Baloglu (2002) presents the loyalty matrix that shows four loyalty levels (segments): high (true) loyalty, latent loyalty, spurious loyalty and low (no) loyalty, based on the cross-classification of attitudinal levels that represents the degree of psychological attachment and the behavioral level that represents repeat patronage.

Customers with high (true) loyalty are characterized by a strong emotional attachment to the company and frequent patronage. Latent loyalty is a strong emotional attachment accompanied by low usage. Spurious loyalty is repeat patronage without emotional commitment, typically motivated by convenience or lack of alternatives. Low (no) loyalty is low patronage and a lack of emotional attachment (Tanford and Baloglu, 2012). Tanford and Baloglu conducted a multivariate analysis of variance on the questionnaire response data of 261 casino loyalty program members in Las Vegas, USA, and attained the validity of the loyalty matrix as follows: true loyalty (36.8%), latent loyalty (28.4%), spurious loyalty (12.3%) and low loyalty (22.6%). Tanford and Malek (2015) demonstrated the validity of the loyalty matrix with hotel customers. They further suggested that the loyalty matrix has utility as a general framework for understanding hospitality loyalty and is applicable to other segments such as restaurants and cruises.

### **Digital strategy case description**

Seven and i launched the cross-group website “Omni 7” in November 2015 and unified the customer ID online. At that time, Seven and i was promoting an “omni-strategy” centered on e-commerce as the group’s digital strategy. However, in 2018, the policy was revised into “a customer relationship management strategy (CRM) that strengthens the relationship with approximately 24 million customers who visit the group stores every day” (Seven and i, 2019a, p. 44). The “Seven Mile Program,” the Seven and i loyalty program, began operating in June 2018. The Seven Mile Program uses the common identifier “7iD” to provide customers with miles according to the quantities purchased and their purchase behavior at each subsidiary of the group and provides rewards through rankings. 7iD also unified the customer IDs of real stores, and customers can use 7iD to log in on mobile apps for the “Seven-

Eleven” convenience store, the “Ito-Yokado” supermarket, and “Omni 7”, which have all been operating since June 2018. Seven and i has announced that by using the common identifier 7iD, the quantity purchased at each subsidiary store will be linked to foster loyalty and promote mutual customer transfer between the real store and the internet. Moreover, the “Seibu and SOGO” department store app was launched in December 2018. As of the end of April 2019, the total number of 7iD members was 14.68 million (Seven and i, 2019a, p. 45).

Using the usage data of the Seven Mile Program, Seven and i performs a customer analysis using six customer segments: “excellent,” “quasi-excellent,” “low-frequency high-purchasing (LFHP),” “high-frequency low-purchasing (HFLP),” “growth” and “entry.” The results of the composition ratio are as follows: excellent 7.5%, quasi-excellent 14.1%, LFHP 7.6%, HFLP 20.6%, growth 37.8% and entry 12.5%. Furthermore, the results of the purchase amount composition ratio are as follows: excellent 30.9%, quasi-excellent 26.5%, LFHP 16.7%, HFLP 12.1%, growth 12.8% and entry 0.8%. Seven and i creates a customer segmentation map every month, captures the movement of 7iD members and plans and implements countermeasures (Ryutsuu News, 2019a, b). As of the end of February 2019, Seven and i had a group-wide store network of approximately 22,400 stores in Japan (Seven and i, 2019a).

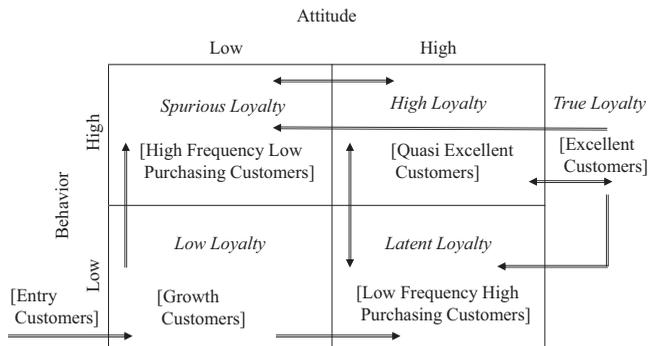
Seven and i initially aimed to accumulate 30 million 7iD members in 2020 by launching the smartphone barcode payment service “7pay” as a new service linked to the Seven Mile Program from July 2019. However, shortly after the service was launched, there were reports of unauthorized access granted to some accounts. The 7pay service was abolished by the end of September 2019 due to several factors, including the time it took to respond to the unauthorized access granted to these accounts (Seven and i, 2019b).

**Model**

*Customer segment transition model through a loyalty program*

We attempt to build the customer segment transition model by integrating the loyalty matrix by Baloglu and the six customer segments of Seven Mile Program members (see Figure 1).

To transform the loyalty matrix from a static stationary model to a dynamic customer state transition model, we add several states to reach true loyalty via high loyalty and to enter the loyalty program. Moreover, we add paths representing customer segment transitions. These paths are drawn using the arrow (tip and line) in this model. The direction of the arrow (tip) indicates the direction (forward-typed or backward-typed) of the time transition of customer loyalty and customer segments through the loyalty program member’s customer experience. The arrow lines indicate the customer experience that triggers the segment



**Figure 1.**  
Customer segment transition model

transition. The correspondence between the customer loyalty categories and the customer segments of the loyalty program shown in this model is described below.

The Seven Mile Program's entry customers first move to growth customers through purchasing activities. Next, they shift to HFLP customers classified as spurious loyalty or LFHP customers of latent loyalty. LFHP customers and HFLP customers can move to quasi-excellent customers who are classified as high loyalty through their customer experience. Reverse cases are also possible: High loyalty's quasi-excellent customers can become excellent true loyalty customers through further customer experience and elapsed time. The opposite case is also possible. In this model, the state change in which both the behavior and attitude—the two dimensions of customer loyalty—simultaneously return to the low level is interpreted as the loyalty program “churn.” Table 1 shows a list of customer experience names distinguished by this model.

### *System dynamics model*

The customer segment transition model can be transformed into a system dynamics (SD) model that performs the numerical time integration. SD is a system modeling and simulation method proposed by Forrester (1961). SD can graphically model a stock variable (cumulative variable), the input/output flow variables that act on a stock and feedback between other variables (circulation effect). As a pipeline structure consisting of stock and flow variables, a cyclical structure combining a customer loyalty promotion chain can also be modeled, representing a chain of different loyalty levels (stock variables) and a demotion chain that includes customer churn (see Figure 2, Figure 5).

### *Stock and flow variables*

The customer segments shown in the customer segment transition model are converted into the SD model's stock variables. The initial value of each customer segment, which is a stock variable including the time term  $t$ , is zero but changes over time due to the influence of customer experience, which is an input/output flow variable. Customer experience appears as a flow variable in the SD model. The formula of stock and flow variables is shown in Table 2.

Transition between customer segments	Customer experience for forward type	Customer experience for backward type
Potential customers, entry customers	New entry	
Entry customers, growth customers	Low loyalty experience	
Growth customers, high-frequency low-purchasing customers	HFLP experience	
Growth customers, low-frequency high-purchasing customers	LFHP experience	
High-frequency low-purchasing customers, quasi-excellent customers	HFLP to high loyalty experience	Backward spurious loyalty experience
Low-frequency high-purchasing customers, quasi-excellent customers	LFHP to High loyalty experience	Backward latent loyalty experience
Quasi-excellent customers, excellent customers	True loyalty experience	Backward high loyalty experience
High-frequency low-purchasing customers, excellent customers		Leap backward spurious loyalty experience
Low-frequency high-purchasing customers, excellent customers		Leap backward latent loyalty experience

**Note(s):** HFLP is high-frequency low-purchasing; LFHP is low-frequency high-purchasing

**Table 1.**  
Customer experience  
segments



Name	Formula/parameter	
Potential customers	$Pc(t)$	(1)
Entry customers	$Exc(t)$	(2)
Growth customers	$Gc(t)$	(3)
HFLP customers	$HFLP_c(t)$	(4)
LFHP customers	$LFHP_c(t)$	(5)
Quasi-excellent customers	$Qec(t)$	(6)
Excellent customers	$Exc(t)$	(7)
Accumulated 7ID members	$Ac7ID$	(8)
Low loyalty experience	$Lle(t)$	(9)
HFLP experience	$HFLPe(t)$	(10)
HFLP to high loyalty experience	$HFLPhe(t)$	(11)
LFHP experience	$LFHPe(t)$	(12)
Backward spurious loyalty experience	$Bsle(t)$	(13)
LFHP to high loyalty experience	$LFHPhe(t)$	(14)
Backward latent loyalty experience	$Blle(t)$	(15)
True loyalty experience	$Tle(t)$	(16)
Backward high loyalty experience	$Bhle(t)$	(17)
Leap backward latent loyalty experience	$Lble(t)$	(18)
Leap backward spurious loyalty experience	$Lbsle(t)$	(19)
Apps withdrawals $i$	$Aw_i(t)$	(20)

$-\int Ne(t) dt$   
 $\int [Lle(t) - LLe(t) - Aw\ initial(t)] dt$   
 $\int [LLe(t) - HFLPe(t) - LFHPe(t) - Aw\ 1st(t)] dt$   
 $\int [HFLPe(t) + Bsle(t) + Lbsle(t) - HFLPhe(t) - Aw\ 2nd(t)] dt$   
 $\int [LFHPe(t) + Blle(t) + Lblle(t) - LFHPhe(t) - Aw\ 3rd(t)] dt$   
 $\int [LFHPhe(t) + HFLPhe(t) + Bhle(t) - Blle(t) - Bsle(t) - Tle(t) - Aw\ 4th(t)] dt$   
 $\int [Tle(t) - Bhle(t) - Lbsle(t) - Lblle(t) - Aw\ 5th(t)] dt$   
 $\int Ne(t) dt$   
 $Exc(t) \times Lle\ rate$   
 $Gc(t) \times HFLPe\ rate$   
 $HFLP_c(t) \times HFLPhe\ rate$   
 $Gc(t) \times LFHPe\ rate$   
 $Qec(t) \times Bsle\ rate$   
 $LFHPe(t) \times LFHPhe\ rate$   
 $Qec(t) \times Blle\ rate$   
 $Qec(t) \times Tle\ rate$   
 $Exc(t) \times Bhle\ rate$   
 $Exc(t) \times Lble\ rate$   
 $Exc(t) \times Lbsle\ rate$   
 $j\ consumers(t) \times Withdrawal\ rate\ i$

**Note(s):** HFLP = high-frequency low-purchasing; LFHP = low-frequency high-purchasing. Let the subscript terms  $i$  and  $j$  be the following ordinal numbers:  $i = \{Initial, 1st, 2nd, 3rd, 4th, 5th\}$ ,  $j = \{Entry, Growth, HFLP, LFHP, Quasi-excellent, Excellent\}$

**Table 2.** Formula for the stock and flow variable

*Aggregation variables*

The customer ratio and the sales ratio in each customer segment are calculated as an aggregation variable for model calibration. The average purchase amount is given as an initial value. The definition formulas using subscript  $j$  and the time term  $t$  are as follows:

$$\text{Total users}(t) = \sum_j \text{customers}(t) \tag{1}$$

$$\text{Total sales}(t) = \text{Total users}(t) \times \text{Average purchase amounts} \tag{2}$$

$$j \text{ customer ratio}(t) = j \text{ customers}(t) / \text{Total users}(t) \tag{3}$$

$$j \text{ total sales}(t) = j \text{ average purchase amounts} \times j \text{ customers}(t) \tag{4}$$

$$j \text{ sales ratio}(t) = j \text{ total sales}(t) / \text{Total sales}(t) \tag{5}$$

*Stationary model and incremental model*

New entry, one option of the customer experience flow variable, is defined as a constant or time variable. When new entry uses constant definition formulas, we refer to a stationary model; when new entry uses variable definition formulas, we refer to an incremental model. The stock variable, potential customers ( $t$ ), is a component of the incremental model. The definition formula of new entry using the time term  $t$  is as follows:

Stationary model:

$$\text{New entry}(t) = \text{Average enrollments} \tag{6}$$

Incremental model:

$$\begin{aligned} \text{New entry}(t) = & \text{Adoption rate} \times \text{Contact rate} \\ & \times \text{Total users}(t) \times \frac{\text{Potential customers}(t)}{(\text{Potential customers}(t) + \text{Total users}(t))} \end{aligned} \tag{7}$$

Formula (27) includes only the internal influence of external and internal influences (Mahajan *et al.*, 1990), which are components of the Bass model (Bass, 1969). The internal influence is included in new entry at this time due to contact between potential customers and existing customers; the same definition formulas apply, resulting from the word-of-mouth effect.

**Results**

*Initial value setting*

Time-series data are analyzed for 48 weeks from June 2018, when the 7iD member service started, to the end of April 2019 (start time, zero; end time, 47). The initial value for average enrollments (212,766) used in the stationary model is calculated by dividing this period's increase in 7iD members. The average purchase amount (JP¥1,808.25) is attained by dividing the 7iD members' average monthly purchase amount (JP¥7,233) by 4 weeks. The initial value of potential customers (4.68e + 06 [Person × Week]) used in the incremental model is set using the number of Nanaco electronic money cards issued by Seven and i as a proxy for the number of users (issued numbers of Nanaco until 2019 × potential diffusion rate). The Euler method of numerical integration is used, and the time interval, where the time step is a week, is set to 0.015625.

*Parameter optimization by model calibration*

The two models are calibrated in two steps, and the parameters are optimized (see Figure 2). The first step is parameter optimization using time-series data of accumulated 7iD members

and customer ratio data for each customer segment. In the second step, after setting the parameter values attained in the first step as initial values, the sales ratio data are used to optimize the average purchase amounts for each customer segment. The modified Powell algorithm is used as the multidimensional iterative calculation method for parameter optimization. This algorithm is a type of conjugate gradient method that uses the payoff function for the squared error between the value calculated and the value of the actual data over the time integration interval with 95% confidence intervals for each parameter, implemented in Ventana System's Vensim software. Table 3 shows the list of optimal parameter values.

The average purchase amounts corresponding to customer segments and/or customer loyalty also increase with the state transition. The LFHP average purchase amounts of latent loyalty are four times higher than the HFLP average purchase amounts of spurious loyalty. Excellent average purchase amounts corresponding to true loyalty are JP¥7,500 per week (JP¥390,000 per year)—twice as much as quasi-excellent average purchase amounts corresponding to high loyalty.

#### Approximate calculation results

Table 4 shows that the approximate results for the accumulated 7iD members have a mean absolute percentage error of less than 10%, representing a high accuracy level (Lewis, 1982).

Names		Stationary model	Incremental model
Potential diffusion rate [Dmnl]			1
Adoption rate [1/Week]			0.0332
Contact rate [1/Week]			1
Low loyalty experience rate [1/Week]	Lle rate	0.08	0.09
HFLP experience rate [1/Week]	HFLPe rate	0.0474	0.0491
LFHP experience rate [1/Week]	LFHPe rate	0.0198	0.0216
HFLP to high loyalty experience rate [1/Week]	HFLPe rate	0.1	0.1
Backward spurious loyalty experience rate [1/Week]	Bsle rate	0.1	0.1
LFHP to high loyalty experience rate [1/Week]	LFHPhle rate	0.1	0.1
Backward latent loyalty experience rate [1/Week]	Blle rate	0.02	0.013
True loyalty experience rate [1/Week]	Tle rate	0.044	0.05
Backward high loyalty experience rate [1/Week]	Bhle rate	0.01	0.015
Leap backward latent loyalty experience rate [1/Week]	Lbllle rate	0.015	0.018
Leap backward spurious loyalty experience rate [1/Week]	Lbsle rate	0.01	0.01
Withdrawal rate initial [1/Week]		0.01	0.01
Withdrawal rate 1st [1/Week]		0.002	0.002
Withdrawal rate 2nd [1/Week]		0.02	0.02
Withdrawal rate 3rd [1/Week]		0.02	0.02
Withdrawal rate 4th [1/Week]		0.02	0.02
Withdrawal rate 5th [1/Week]		0.02	0.02
Entry average purchase amounts [Yen/Person]		70	70
Growth average purchase amounts [Yen/Person]		600	600
HFLP average purchase amounts [Yen/Person]		1,000	1,275.46
LFHP average purchase amounts [Yen/Person]		4,000	4,600
Quasi-Excellent average purchase amounts [Yen/Person]		3,200	3,500
Excellent average purchase amounts [Yen/Person]		7,500	7,500

**Note(s):** HFLP = high-frequency low-purchasing; LFHP = low-frequency high-purchasing

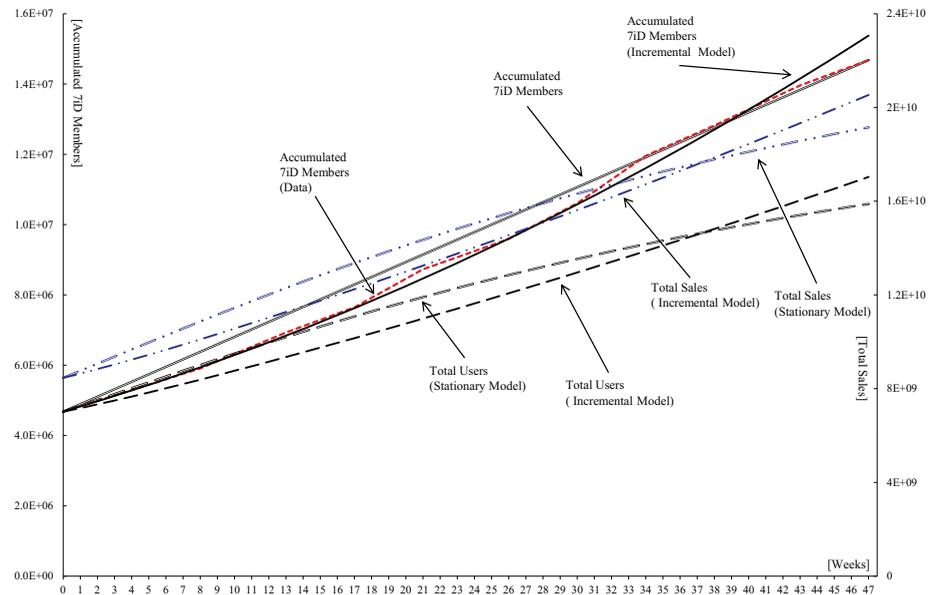
**Table 3.**  
List of optimum  
parameter values

	Stationary model	Incremental model	Data (estimated values)
Period [Week]	48	48	48
Coefficient of determination ( $R^2$ ) of accumulated 7iD members	0.9844	0.9959	
MAPE of accumulated 7iD members	4.07 %	1.17 %	
Entry customers ratio	0.2264	0.2467	0.125
Growth customers ratio	0.2684	0.2699	0.378
HFLP customers ratio	0.2125	0.2037	0.206
LFHP customers ratio	0.0716	0.0663	0.076
Quasi-excellent customers ratio	0.146	0.139	0.141
Excellent customers ratio	0.075	0.0744	0.075
Entry consumers sales ratio	0.0088	0.0095	0.008
Growth customers sales ratio	0.0891	0.0896	0.128
HFLP customers sales ratio	0.1175	0.1437	0.121
LFHP customers sales ratio	0.1585	0.1685	0.167
Quasi-excellent customers sales ratio	0.2584	0.269	0.265
Excellent customers sales ratio	0.3109	0.3088	0.309
Total sales [Thousand Yen]	19,146,947	20,537,805	

**Note(s):** HFLP = high-frequency low-purchasing; LFHP = low-frequency high-purchasing; MAPE = mean absolute percentage error

**Table 4.**  
Approximate calculation results of aggregated sales performance

Table 4 also shows a list of approximate values of the performance indicators at week 47 attained from time integration. In this case, the ratio values for each customer segment announced by Seven and i, as a result of customer analysis, were used as the data (estimated value) for the 47th week. Both models calculate a good approximation of aggregated sales performance for excellent customers and quasi-excellent customers. Figure 3 shows the transition of the accumulated 7iD members for the stationary model and the incremental model.



**Figure 3.**  
Comparison graph of stationary and incremental models (48 weeks)

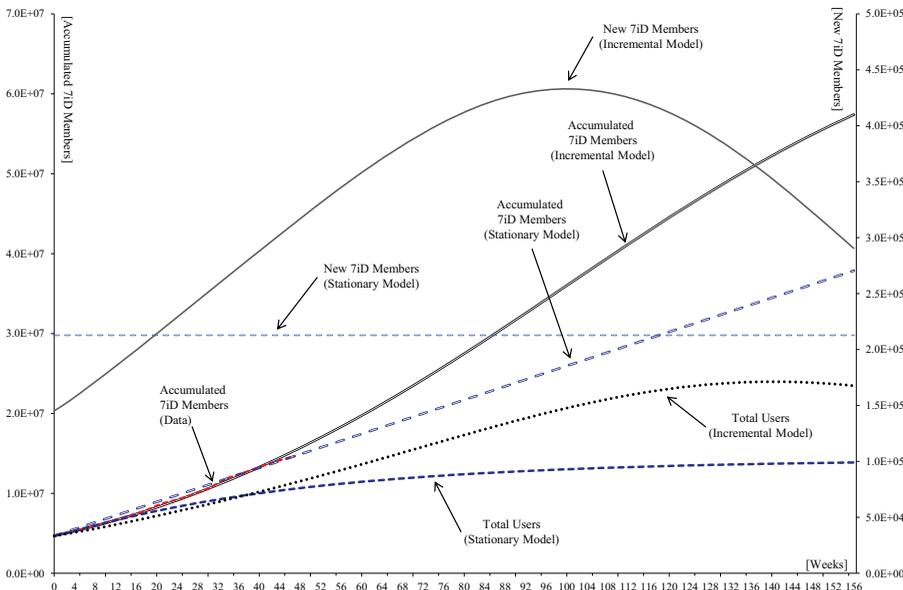
The incremental model better approximates the mean and trend of time-series data of accumulated 7iD members over the 48 weeks than the stationary model. However, the difference from time-series data has been increasing since week 40. In contrast, the stationary model is a linear approximation and calculates a greater value until week 32 but calculates a good approximation after week 33. Thus, for forecasting after week 47, it may be possible to attain more appropriate prediction results from the stationary model than the incremental model. This study uses both stationary and incremental models for forecasting.

*Base-case scenario forecasting*

Predicted values extended from the approximate calculation results for 48 weeks using the stationary model and the incremental model to 156 weeks are shown as the base-case scenario (see Figure 4). In both models, new 7iD members represent new entry. In the stationary model, the new 7iD members, the accumulated 7iD members and the total users are increasing monotonically, and the maximum value is reached in the final week (week 156). In the incremental model, the maximum value of the new 7iD members (433,032) is reached in week 100 (the first week of May 2020). The difference in the accumulated 7iD users in week 156 between the stationary model (37,871,496) and the incremental model (57,381,172) is approximately 19.51 million members. The difference in the total users in week 156 between the stationary model (13,869,516) and the incremental model (23,467,598) is about 9.6 million users.

*Sensitivity analysis with pink noise*

Informed by the scenario described above, predictive analytics are now used to forecast customer segment transition (June 2018 to May 2021) in the case that a new barcode settlement service, 7pay, continued to operate from July 2019 (week 57).



**Figure 4.** Comparison graph of stationary and incremental models (157 weeks)

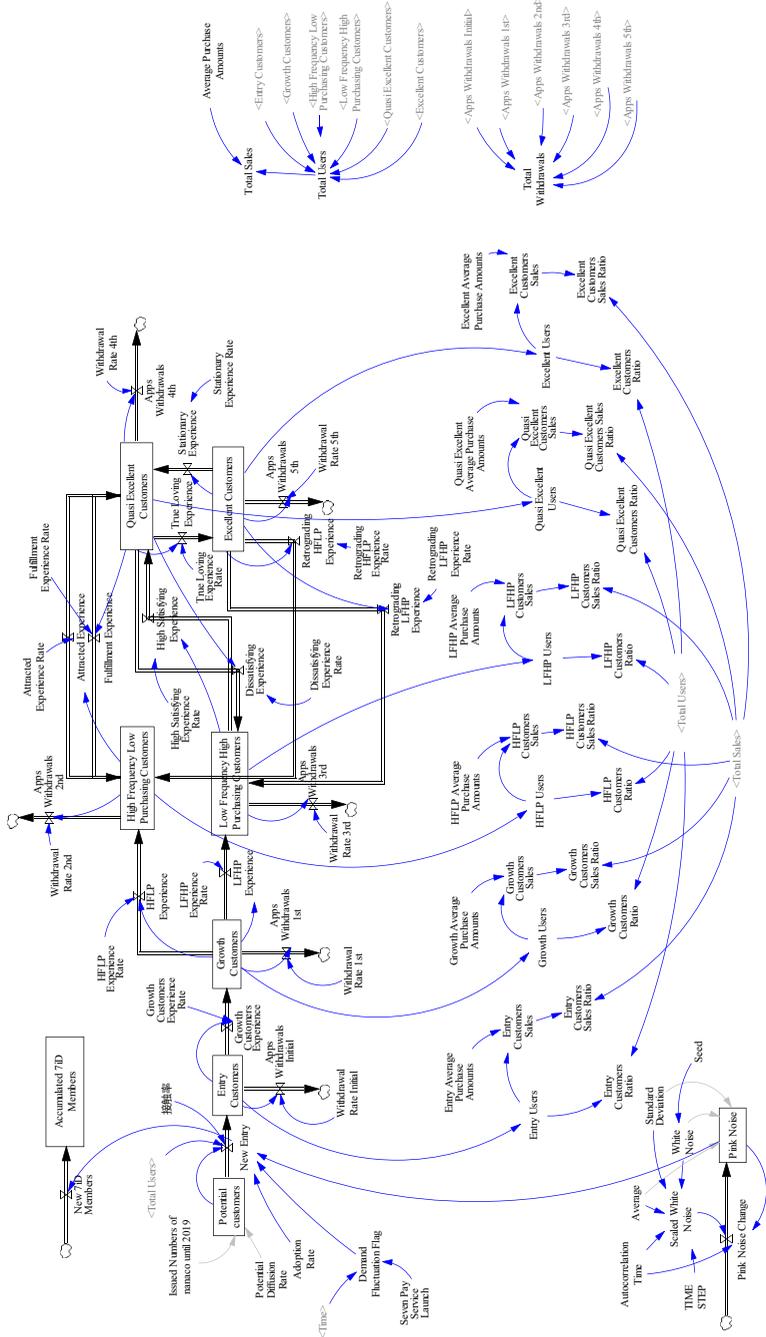


Figure 5. Incremental model with pink noise

Complicated processes, such as changes in consumer behavior and organizational processes over time, can be modeled as a pink noise model (Dooley and Van de Ven, 1999). Pink noise can be set as a component (variable) of the SD model for the demand fluctuation (Deif and Elmaraghy, 2009). To do this, sensitivity analysis is performed from week 57, using modified versions of the stationary and incremental models so that pink noise is multiplied as the fluctuation scale of the “New entry” (see Figure 5). A simple formulation of pink noise is first-order exponential smoothing (first-order autocorrelation noise) using white noise. The definition formulas for pink noise generation with normally distributed random numbers as white noise ( $t$ ) at time  $t$  are as follows (Sterman, 2000):

$$\text{Scaledwhitenoise}(t) = \text{Average}$$

$$+ \text{Whitenoise}(t) \times \text{Standard deviation} \times \sqrt{\left( \frac{2 - \frac{\text{Timestep}}{\text{Autocorrelationtime}}}{\frac{\text{Timestep}}{\text{Autocorrelationtime}}} \right)} \tag{8}$$

$$\text{Pinknoisechange}(t) = (\text{Pinknoise}(t) - \text{Scaledwhitenoise}(t)) / \text{Autocorrelationtime} \tag{9}$$

$$\text{Pinknoise}(t + \text{Timestep}) = \text{Pinknoise}(t) - \text{Pinknoisechange}(t) \tag{10}$$

$$\text{Pinknoise}(0) = \text{Average} + \text{Standard deviation} \times \text{Whitenoise}(0) \tag{11}$$

The following values are set as initial values for sensitivity analysis: Seed = 10 and Autocorrelation time = 4 [Week]. The seed is a set value that allows for the generation of a normally distributed random number. A Monte Carlo simulation, in which the values of the average and standard deviation for the scaled white noise setting are changed with uniform random numbers, was executed 1,000 times. The range of both variables is as follows:  $0 \leq \text{standard deviation} \leq 1$ , and  $0.5 \leq \text{average} \leq 1$ .

From the sensitivity analysis results, the lower and upper limits of performance indicators at week 156 (three years later) are estimated according to the following procedure. The lower limit value is calculated by applying sensitivity analysis to the stationary model with pink noise, and the upper limit value is calculated as the 97th percentile value by applying the sensitivity analysis to the incremental model with pink noise. This corresponds to the combination of 95% confidence intervals in the sensitivity analysis of the two models. The lower and upper limits of each performance indicator can be interpreted as the worst-case and the best-case scenario, respectively. For the base scenario, the stationary model is selected because it gives a lower value. Table 5 shows a list of performance indicator values

	Worst-case scenario	Base-case scenario	Best-case scenario
Period [Weeks]	157	157	157
New 7iD members	130,613	212,766	339,232
Accumulated 7iD members	29,086,978	37,871,496	60,223,368
Weekly total users	9,214,877	13,869,516	26,658,408
Quasi-excellent customers	1,688,943	2,470,685	5,028,673
Excellent customers	1,361,950	1,926,458	3,584,130
Quasi-excellent customers ratio	17.3%	17.81%	19.06%
Excellent customers ratio	12.6%	13.89%	14.77%
Quasi-excellent customers sales ratio	30.6%	31.52%	36.90%
Excellent customers sales ratio	52.4%	57.61%	61.26%
Total sales [Thousand Yen]	16,662,800	25,079,600	48,205,100

**Table 5.**  
Estimated values of  
aggregated sales  
performance in the  
medium-term forecast

for the worst-case, base-case and best-case for a medium-term forecast. In these estimated values, the quasi-excellent customers' ratio will be between 17% and 19%, and the excellent customers' ratio will be between 13% and 15%.

Meanwhile, the sum of the quasi-excellent and the excellent customer ratios is about 30% in each scenario, which is consistent with the empirical results of [Tanford and Baloglu \(2012\)](#) for true loyalty (36.8%) and seems to be a reasonable and achievable target value.

### Discussion and conclusion

Of the medium-term forecasts shown in [Table 5](#), the worst-case scenario corresponds to the 7iD forecast for FY2020, presented by Seven and i Holdings. From the dynamic model in this study, a higher number of 7iD members and aggregate sales performance are expected as the base-case scenario. While their numerical targets are solid, they may underestimate the size of the new market that will result from the diffusion of retail group-scale loyalty programs using smartphone apps.

[Grewal and Roggeveen \(2020, p. 7\)](#) state that "in the coming years, it will be of paramount importance for every retailer and service provider to have a systematic and integrated customer journey model (CJM) system in place." Meanwhile, it is also important to build and forecast an overall "customer journey" (CJM) model (aggregated sales model) from a systemic perspective as digital strategy measurement ([Adner et al., 2019](#)) to leverage the big data. The customer IDs (7iD) for brick-and-mortar stores and the loyalty program (Seven Mile Program) for smartphone apps described herein are advanced examples of digital strategies in the retail industry.

However, if the number of customers had been tracked using a dynamic model such as the one presented in this study, their market size forecast would have been different. This model takes account of the iterative transition of customer loyalty segmentation from the systemic perspective of the customer journey and the approximate calculated result of the segmented group size of loyalty program members; total performance is highly accurate. Furthermore, it can predict factors including the uncertainty of the market size. These presentations are the theoretical contribution of this study.

The research implication of this study is that the retail industry's digital strategy should be more focused on estimating and forecasting the average amounts of customer segments and the number of aggregated customers through the digitalization on the customer side than individual customer journeys and responses. This suggestion is consistent with previous research stating the key features of digital strategy are connection, aggregation and focus on forecasting ([Adner et al., 2019](#)). Modern retail companies tend to collect big data, perform statistical analysis and seek to attain insights from the results ([Santoro et al., 2019](#)). However, there may not be much interest in understanding and managing customer journey from a systemic view by developing and executing a dynamic model. The practical implication of this study is that multi-scenario evaluation through simulation of dynamic models from a systemic view can be used for decision-making in retailing digital strategies.

The limitations of this study provide opportunities for future research. This study sets several kinds of customer experience rates, by calibration. The formula for them might be defined by multiple explanatory variables. Additionally, in this study, we could not prepare the data to prove the validity of the range of the initial value (mean and standard deviation) of pink noise for market size prediction. Thus, there is scope for future research to address these matters.

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