Why passenger rather opts for self-service at the airport:
Discussing how ABM effectively explicates the real world

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Abstract– There are various methodologies to explain the complex world. Many studies have tried to explicate the real world with data, with better methodologies, and through the experiences. We examine how individuals decide to use self-service technology. The decisions made by individuals between options of service are to be located in various contexts, including that of their traits. We focus on the check-in process for air travelers at the airport and map the real existing world onto the experimental space to represent the decision-making process in an agent-based model(ABM). Real-world data, taken from an airline's system, is used to verify and validate the model. A cognitive model is implemented in ABM, which utilizes a fuzzy inference system to model each agent's choice. Passenger behavior is carefully designed based on the knowledge of experienced front-line airport customer-service experts and is also reviewed and clarified by on-site observations. We also discuss effectiveness of ABM in comparison with the statistical model.

Keyword: agent-based modeling(ABM), simulation, fuzzy,self-service technology, airport, airline, innovation

1 Introduction

1.1 Background

Developed countries, such as the G7, are facing a future in which they will need to deal with their aging societies. With better health care and fewer children, industries are securing their workforce in new ways. In these countries, the service industry's share of economic activity and employment is increasing; the so-called "service economy " continues to develop.

Someone or something is required to offer better service and interact with consumers. Self-service technology (SST) is a promissing alternative for the future of the service workforce. In this study, we focus on self-service kiosks at the airport, as these are a familiar alternative travelers can take to check-in.

1.2 Purpose of this study

ABM models the essence of the real world which we construct in the experimental space. It contains the various knowledge from observation of the real world. We pursue how ABM methodology explicates individuals opt for SST at the moment of decision-making by refining the previous work. This study examines observable external facts and invisible, internal factors, which include the history and traits of the individual to understand how consumers opt for SST. In order to understand the dynamic mechanism of decision-making, we implement a new conceptual model using agent-based modeling (ABM), which illustrates the behavior of the adoption of SST, specifically on the use of a self-service kiosk at the airport. In addition, we try to extend our discussion how the effectiveness of ABM will be illustrated by compared with the statistical model.

2 Related work and subject

SST has been examined in various perspectives. We review innovation studies, as SST adoption is an individual decision to take a new way. The service-marketing field is given an overview to understand the development of SST studies. Then we review agent-based modeling, as a tool to explicate the dynamics of the phenomenon of SST adoption.

2.1 Innovation diffusion

Innovation is defined as the introduction of something new:a new idea, method, or device. However, innovation is often also viewed as the application of better solutions to meet new requirements, unarticulated needs, or existing market needs. This is accomplished through more effective products, processes, services, technologies, or business models that are readily available to markets, governments and society.

Rogers (1983) designated variables to define the speed of diffusion. More relative advantage, higher compatibility, less complexity, higher trialability, and greater observability speed up the diffusion of innovation. The role of the change agent in promotinge innovation is an important variable increasing the speed of the diffusion[12)].

Since SST adoption is an individual decision to accept innovation, variables enhancing the diffusion speed indicate what we should look at for this study.

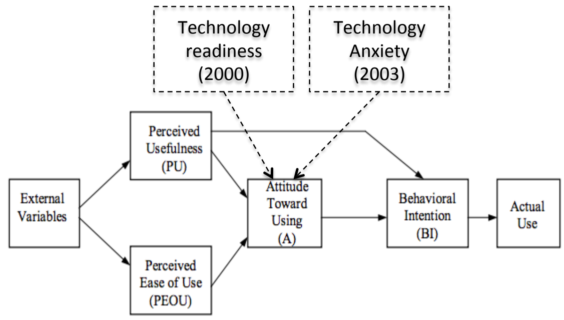

Fig. 1: Technology Acceptance Model [1]

2.2 Service-marketing framework

Convenience has been examined and discussed from two main perspectives: 1) wait time and its management and 2) what consumers find convenient [1)]. There are studies that have found factors that influence the usage of SST through various means, both surveys and interviews. Meuter, Ostrom, Roundtree and Bitner (2000) concluded that service convenience through SST brought consumer satisfaction when it was "better than the alternatives" and they appreciated "time saving" the most [10)]. They also concluded that SST usage depends on customer readiness for SST[2)].

Davis(1989) proposed a technology acceptance model[5)](Fig.1). He concluded that perceived useful-

[1]Concepts of consumer readiness and technology anxiety are added by the authors.

ness and ease of use create attitudes toward SST. Liljander, Gillbert, and van Riel (2006) reviewed SST adoption in the perspective of consumer readiness. Another study concluded that technical anxiety explains the influence of SST adoption better than the demographics of users [11].

Dabholker[4] proposed an extended attitudinal model of self-service technology, which clarifies the moderating variables affecting attitude toward and intention to use SST. This model shows that consumer traits and situational factors can slow down SST usage or prompt it (Fig.2).

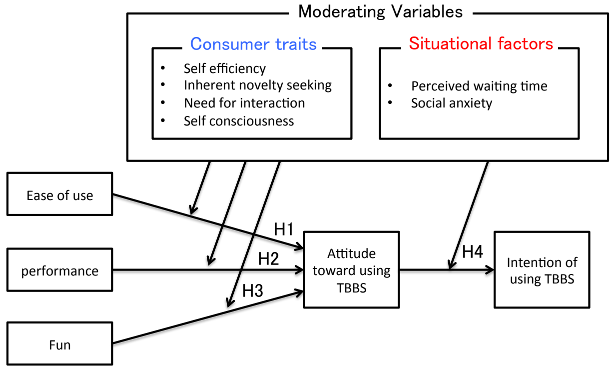

Fig. 2: An Attitudinal Model of TBSS(technology-based self-service)

2.3 ABM

ABM is based on technical instruments, that enable each agent to behave autonomously. Agent-based simulation is developed through placing players in experimental space and approximating the experimental space to the real world. A social multi-agent system shows phenomena in complex social systems [8]. Kawai built an abstract model to explain the diffusion of the services using ABM[7].

These studies indicate important facts and concepts for the diffusion of innovation. However, they merely illustrates the concept, but do not reproduce the mechanism of decision making at the moment when one out of several options is chosen. As Kawai's model does not use observed data from the real world, it remains to show the concept but it fails to represent the actual phenomenon of diffusion and what makes consumers select a new alternative.

By mapping the real world in the experimental space using airline data, Ueda and Kurahashi (2012) created ABM that demonstrates how air travelers choose self-service kiosks at the airport[14] (Fig.3). Their model illustrates the mechanism of SST adoption at the moment of selecting one of two options.

This model uses a fuzzy inference methodology for each created agents in the experimental space. Experienced airline staff defined simple rules (Table 1). The implement model calculates the self-service preference index(*SPI*) at the moment of decision-making. Each agent refers to its own *SPI* score to descide which direction to take (Fig.4).

SPI quantification is constructed from two main components. One copies the real world in experimental space. Passenger agents (represented by turtles) are created with the same timing with which real-world passengers arrived, according to passenger activity records. Each agent is given a variable with a random value, which represents that agent's hesitation to accept novelties. The other obtains membership scores in the experimental space. Agents move

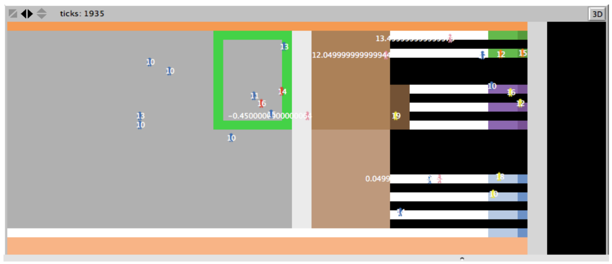

Fig. 3: Self-service Adoption model in airport

toward the conventional check-in area as their first choice. When an agent reaches decision-making area, it counts the number of turtles already queuing infront of check-in options to estimate the waiting time for this check-in area. It calculates the difference between expected queuing time for the conventional check-in area and for the self-service kiosk; thus it perceives whether its default option has a shorter waiting time (membership score W). It perceives the existence of self-service kiosk, recognizing that kiosks are there and they are for check-in (membership score V). In the application of the rules shown in Table 1 results are calculated using the max-mini inference method and the simplified centroid method for defuzzification combines these results.

Table 1: Fuzzy Rules

Rule 1	IF W is short and V is low, THEN *SPI* is negative.
Rule 2	IF W is long and V is high, THEN *SPI* is positive.

Score W: Waiting time for conventional check-in
Score V: Visibility of self-service kiosk

The input value for calculating W is defined by equation (eq.1). *EQT* is the predicted difference in waiti time at the conventional check-in, the wait time for using the self-service kiosk. *NCCQ* is the number of passengers waiting in the conventional check-in queue. *CCPs* is the number of conventional check-in positions. *NSSQ* is the number of passengers waiting in self-service queue. SSU is the number of self-service units. Finally, *p1* and *p2* are the weighting parameters for each members of the equation. If the preference is the same between two options, they have same value; however, few passengers prefere the self-service kiosk.

V reflects how the passenger perceives self-service kiosks. V is low where there are no passengers using self-service kiosks. As more passengers use self-service kiosks, the value becomes higher. Once the number of passengers who are using self-service kiosk exceeds the number of self-service kiosks, V is reduced, because if many passengers occupy the self-service area, visibility of the self-service kiosks significantly deteriorates.

$$EQT = \left(\frac{NCCP}{CCPs}\right) \times p1 - \left(\frac{NSSQ}{SSUs}\right) \times p2 \qquad (1)$$

Airport staff interaction leading passengers to SST use is viewed positively[3)6)], this model locates customer-service agents in the check-in lobby of the experimental space.

Passenger agents must go through the designated area in order for customer-service agents to try for interacting with them. Customer-service agents try

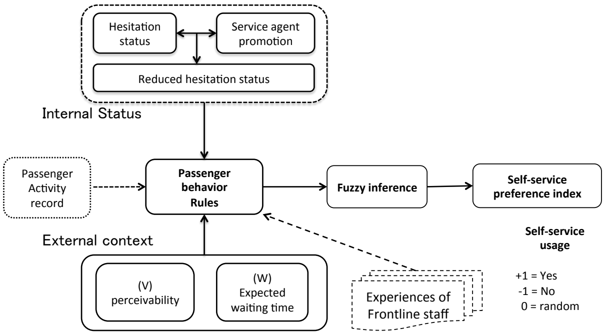

Fig. 4: Self-Service Preference Index

to catch passenger agents as many as possible to guide them to SST. Once the passenger agent makes contact with the customer-service agent, its ingernal status, the hesitation, over using SST is reduced.

The model creates a passenger agents at the same time as passenger actually arrive according to airline system records, and it locates productive properties such as check-in position, self-service kiosks and customer-service staff in the same amounts, as shown in Table 2, 3.

Verification and validation were done carefully with one dataset for training out of six datasets. After fitting the parameters using the training data, we conducted experiments using the other datasets. In each experiment, the number of check-in counters and staff are mapped as the same way as the passenger boarding times. In addition, various parameters are set to map the real world, such as *baggage holder rate* (0.7), *frequent self-service user rate* (0.05), *non-self-service user rate* (0.2), and the *processing time* for the different service options (interpersonal service, self-service, and baggage check-in).

In these experiments, we observed a *self-service usage rate*: the quotient of passengers using self-service divided by all passengers. The result of simulation showed a less than 3% RMSE(Root Mean Squared Error) in *self-service usage rate* versus the real data. This is persuasive for the modeling actual passenger handling for managers at the airport.

Table 2: Experimental Dataset

	Passenger choice		Product property			
Data	IPSC	SSC	SSU	Ckin	Bag	STF
406	85	46	4	3	3	2
408	100	60	4	2	3	2
409	68	39	4	2	2	3
410	67	54	4	2	2	3
411	63	62	4	2	2	3
412	67	25	4	3	2	0

IPSC: interpersonal Service (conventional)
SSC : self-service
Ckin: check-in
Bag: baggage check-in
STF: custemer service agent
Dataset 412: training dataset

2.4 Subjects of related works

Innovation studies describe how people introduce new way. The literatures in the service-marketing field specifies and explores factors that have the effect of promoting the use of TBSS. Such studies are based on statistical methods using the past data. The analysis is static, not dynamic.

Dabholkar et al.(2002) concluded that situational factors and consumer traits have a direct effect on promoting a positive attitude towards TBSS and the intention to use TBSS. However, if one situational factor changes, the results would also alter as Dabholkar noted. Works in this field have not illustrated the mechanism by which predictable results can be reliably reproduced.

Our proposed ABM, a model of self-service adoption at the airport, supports the concept of technology readiness and technology anxiety. It demonstrates the dynamic mechanism of SST adoption in the moment of passnger decision of how to check-in to a flight. However, the proposed ABM has not yet introcueded the traits of individual which are moderating variables that establish attitudes towards using SST [4].

We introduce the concept of moderating variables into our ABM in the context of choosing one service. And we need to extend our discussion that the effectiveness of ABM, which could enhance the explanatory capability of other analysis models.

3 Refining the SST adoption model

We replicated the implemented ABM [14], a model of self-service adoption at the airport with the addition of the concept claimed by Dabholkar et al (2002). This new concept is described in 3.1 and how it comes to be implemented in ABM is explained in 3.2.

3.1 Concept expansion

Passengers are influenced by several factors when they choose a check-in option, such as their previous flight experiences, the queue length, how self-service kiosks and their surroundings appear, and their travel conditions (volume of baggage, number of passengers in their party, etc.). It has also been observed that the guidance and support of customer-service staff promotes the use of self-service kiosks. We organized a decision-making conceptual model for self-service kiosk usage(Fig.5).

Demographic data, travel conditions, and the historical record of departing passengers were collected from an airline. We explore and examine the efficient factors that influence SST usage by aggregate analysis, which we discuss in 4.2.

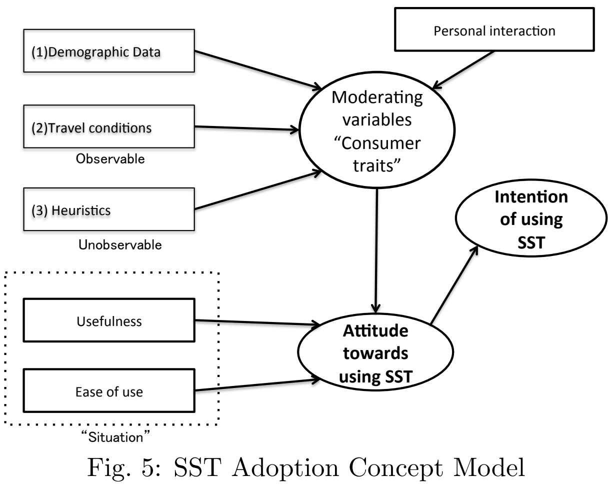

Fig. 5: SST Adoption Concept Model

3.2 ABM implementation model

Departing passengers must check in for their flight. It is important to them not to have their time constrained by others.

Usefulness is defined as expectation of reduced waiting time in comparison with conventional check-in queuing time and Ease of use is defined as the passenger being able to see the kiosk and recognize that it is functioning.

The ABM can allow the agent to move and queue for either service options and count how many agents are located in each queuing line. Waiting time and perceiving whether the kiosk is functioning both influence whether the air traveler chooses SST. The situation is different at every moment, because the timing of the passenger's arrival creates queuing lines and it is unclear who will choose which option. We map real-world data onto the experimental space, including passenger traits that have not been introduced in previous work.

4 Experimental results and discussion

The details of datasets for the experiments with the replicated ABM are described in 4.1. The traits of the passengers are mentioned in 4.2. The result of experiments is discribed in 4.3.

4.1 Datasets

Passenger data was extracted from an airline's system. This data consist of demographic data ,travel conditions, flight records, and chosen check-in options(Fig.6).

We examined *DatasetB* carefully and passengers were categorized into three types. 35.2% of them are weak SST users: they seldom use SST; 14.8% of them have a strong preference for SST; and 50% of them are neutral.

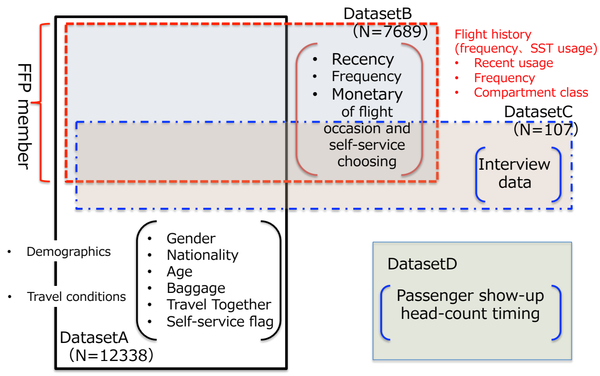

Fig. 6: Dataset for experiments

4.2 ABM experiment

We verify the refined ABM model of self-service adoption at the airport by observing the model's behavior and validating it with the training data from *DatasetD* (described in Tables2, 3 and Fig.7 as dataset412).

The validation process is conducted by calibrating the parameters. We find the closest value for *self-service usage rate* to the real world by adjusting the *speedmax* (one of the parameters) in 0.01 increments and running a simulation. The difference between the simulation results and the real world is smallest when the *speedmax* value is 0.21. The same process is conducted with the parameter *p1*. A parameter value 5.0 brings the result that is closest to the real world.

After setting the parameter values, we execute an experimental 50 runs each for five test datasets with different circumstances to observe the *self-service usage rate*. The tested datasets vary in the timing of passenger arrival; they are completely different. The experiments adjust the number of service staff, check-in positions, and self-service kiosks to map the same circumstance as the day and time which each dataset was extracted. The experiment results in the replicated model shows that the RMSE of simulation vs real data is less than 4%(Table 3,Fig.7).

Table 3: Experimental Results

	Product property					
Data	Ckin	Bag	STF	SIM	real	RMSE
406	3	3	2	0.373	0.351	0.022
408	2	3	2	0.417	0.375	0.042
409	2	2	3	0.350	0.364	0.015
410	2	2	3	0.419	0.446	0.027
411	2	2	3	0.409	0.496	0.087
412	3	2	0	0.285	0.272	0.013

average of RMSE for test result : 0.0385
SIM : average results of simlation

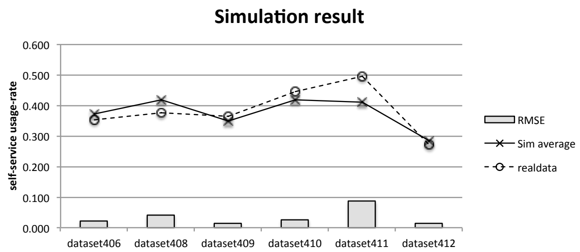

Fig. 7: Experimental Results

4.3 Discussion

The previous ABM creates passenger agents and gives a random score of the variable, representing the concept of "Technology Anxiety" to each of them. Once a passenger agent comes into contact with service agent, the value for this variable is reduced .

The replicated model stochastically adds individual traits to each passenger agent. When the refined ABM creates passenger agents, each agent has a self-service preference, reflecting the proportions of each category of passenger as shown in 4.1. In other words, the replicated model implements a new heuristic variable that contains each individual's historical experience, including SST usage and number of flights. Though the RMSE of the replicate model experiment (RMSE < 0.039) is relatively larger than that of the original model (RMSE < 0.03), it is practically accurate enough for on-site managers. As giving stochastic traits was a major change from the previous model, it may expand the variance of the results. We were able to improve how we categorize passenger traits for future research.

Passengers select the most feasible option from their immedeiate perception of their surroundings. It is obvious that queuing time is a key to determining the attitudes towards self-service kiosks, because passengers value their time. In the parameter-validation process of ABM, calibration results indicate what could be done to promote the use of self-service kiosks at the airport.

Our experiments show that each parameter works differently. One agent parameter, *speedmax*, has a linear relation to the *self-service usage rate* (Fig.8). Other parameter, the weighting parameter of interpersonal service preference (*p1*), has a non-linear relations to the *self-service usage rate*(Fig.9).

The graphs show that the results of calibration of *speedmax* have less variance than *p1*. It appears that even though an individual's mind-set could change, this does not control the outcome of their behavior. However, this means that if we can control the

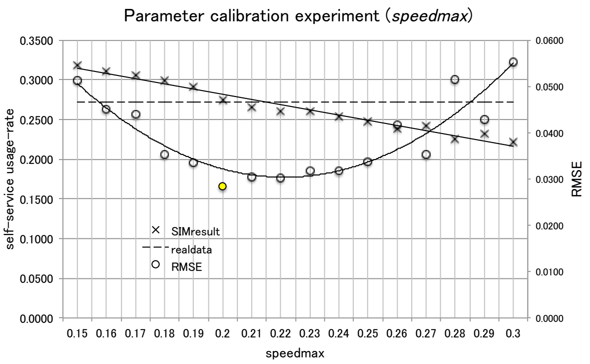

Fig. 8: Parameter fitting:speedmax

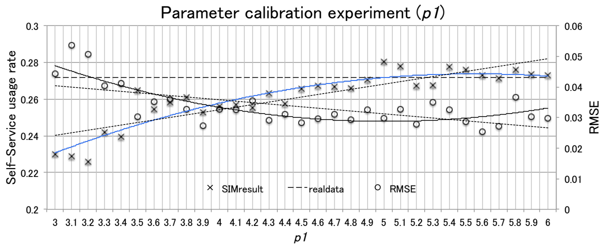

Fig. 9: Parameter fitting:p1

speed that individuals move, we may promote SST usage more effectively than trying to change individual traits. If we let passengers have more time to recognize and compare their options, they might choose SST more often. We would have greater ability to reduce individual and overall wait time by changing the factors in the environment, such as passenger flows.

ABM is powerful tool for reproducing the dynamic situations created by the interaction of decision makers. The replicate model quantitatively supports the conceptulization of Dabholkar et al. (2002), with an average RMSE less than 0.04 versus the real-world results. Through the replicating process using ABM, we were able to learn how selected parameters affect outcomes by observing behaviors and employing sensitive analysis.

5 Validation of ABM

In the previous chapter, we described our model's advantage, which considers dynamic decision making mechanism, timing, location of air-traveler and interaction between heterogeneous agents. These are well-known characteristic of ABM, however, we have not yet stepped in to examine that those characteristics work more effectively as an advantage of ABM than other analysis model. In this chapter, we discuss the methodology of validating the effectiveness of the ABM proposed model. We describe the concept how we illustrate the effectiveness of ABM; which is how ABM enhances the explanatory capability of other analysis model.

5.1 Assumption

ABM is a powerful instrument and mehodology to represent the real world. It can let each agent's detect the surrounding situational factors of them, which varies time by time and includes the interactions of agents in the experimental space. ABM has a strong advantage to reproduce the phenomenon by mapping the real world. The well-examined essence of the real world can be mapped to the experimental space to simulate and analize the complex system.

The issue of our study contains three major behaviors. Firstly, in the context that passenger chooses a check-in service opted out of two, they follow a simple common rule. Secondly, it is observed, there are three behavior types: passenger who likes the interpersonal service, passenger who rather uses self-service kiosk, passenger who decides the option depending upon the situation. Each passenger has different traits, feels and thinks differently, but we can't see what it is from outside. Thirdly, the passenger has a certain measure of value to accept new way, which is accepting and using the self-service kiosk. There are moderating factors towards using self-service technology, which works either positively or negatively. The lobby service agent may reduce the hesitation of using self-service kiosks by encouraging passenger and advising them that those machines are working and telling them new process is rather quicker than the other way.

The objective variable of our study is either using or not using self-service, which means it deal with boolean categorical data. We analyze the data from the same source by logistic regression analysis and ABM, and discuss how we can compare and explicate the advantage of ABM with careful consideration of those three topics.

5.2 preliminary experiment and preparing the datasets

In this section, we describe the concept of the ABM effectiveness measurement, explain the comparison object to be prepared and the way how we examine it. Section 5.2.1 describes the result of what variable explains passenger choice of self-service significantly by using logistic regression analysis. Section 5.2.2 gives an overview of the verification method, and explains the data used for verification.

5.2.1 Logistic regression analysis

We randomly selected 400 samples from *DatasetB*, which contains equal numbers of SST users and non-users.

Regression analysis found that travel conditions, such as volume of baggage or traveling in a group, do not influence opting for SST.

```
Call:
lm(formula = SSUflag ~ Gender + Age10 + Bag + Trvltoge + ssuRecency +
    flightFreqClass + C21 + C31 + Density_Wizin15min, data = DSBsample)

Residuals:
     Min       1Q   Median       3Q      Max
-1.04560 -0.40138 -0.00027  0.41119  0.96950

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -1.550e-01  2.617e-01  -0.592 0.554139
Gender              6.591e-02  7.697e-02   0.856 0.392361
Age1010s            3.390e-01  3.307e-01   1.025 0.305965
Age1020s            4.419e-01  2.442e-01   1.810 0.071137 .
Age1030s            2.708e-01  2.408e-01   1.124 0.261556
Age1040s            2.798e-01  2.423e-01   1.155 0.248775
Age1050s            1.346e-01  2.421e-01   0.556 0.578555
Age1060s            2.061e-01  2.423e-01   0.851 0.395330
Age1070s            1.392e-01  2.811e-01   0.495 0.620636
Bag                 7.706e-05  2.540e-03   0.030 0.975814
Trvltoge            2.510e-01  1.060e-01   2.367 0.018404 *
ssuRecency          1.154e-01  1.536e-02   7.516 4.00e-13 ***
flightFreqClass    -9.246e-02  2.036e-02  -4.541 7.51e-06 ***
C21                -1.764e-01  8.786e-02  -2.008 0.045348 *
C31                 4.256e-02  3.057e-02   1.392 0.164617
Density_Wizin15min  1.637e-03  4.261e-04   3.843 0.000142 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4502 on 384 degrees of freedom
Multiple R-squared:  0.2217,	Adjusted R-squared:  0.1913
F-statistic: 7.292 on 15 and 384 DF,  p-value: 3.355e-14
```

Fig. 10: Regression Analysis

Recent use of self-service is the biggest influence for choosing self-service and frequency of flight occasion is second. *C21* is the interaction of baggage and travel in a group. Regression analysis states that the congestion, (variable name: *Density_Wizin15min*), of the check-in lobby is significant in explaining the use of

SST. This data is calculated accumulating the number of passengers within 15min timeframe to which each agent belongs (Fig.10).

The record clearly states that once a passenger's flight frequency reaches the premier customer status in the Frequent Flyer Program, they seldom use SST any more. This is understandable, because such passengers have the privilege of accessing first class check-in where they don't have to wait.

Logistic regression analysis of sample data shows the rate of this prediction's being correct to be 70%.

5.2.2 Overview of validation and preparation of datasets

We compare the results of logistic regression analysis with the results of ABM experiments and verify the effectiveness of ABM. The extracted data from the ABM experiments is used, which has the same condition as the data used for logistic regression analysis.

As mentioned in the previous section, there is an issue that we needed to create approximated context, passenger traits in similar situations. We utilize the advantage of the ABM to deal with this issue. Since AMB can repeat experiments and obtain the results in various patterns, we conduct numerous simulations and extract the data which has the same combinations as the logistic regression analysis result has. Then we observe whether the ABM explicates the decision making process of the individual more effectively by comparing two results between the logistic regression analysis and the ABM.

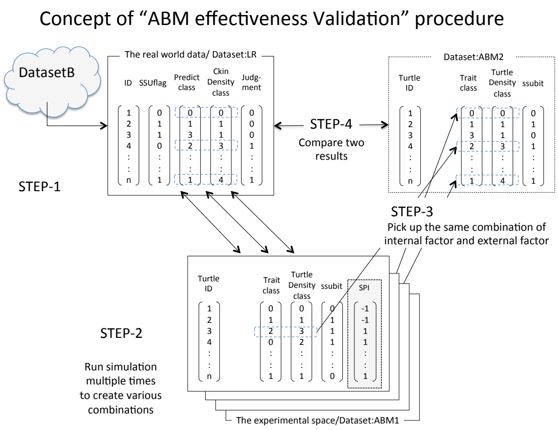

Fig. 11: ABM validation procedure

The experimental procedure of ABM effectiveness validation is illustrated in the following four steps (Fig.11).

STEP-1: We randomly extract the passenger data to form a new dataset (*Datasets:LR*). The constituent elements of *Datasets:LR* include ID that identifies the passenger, and the actual result use/non-use of self-service kiosk ("*SSUflag*"), Check-in time, and "*CkinDensity*" that means a congestion degree of departure lobby. It also includes the predicted values whether the passenger use self-service kiosk, which are calculated from logistic regression analysis and they are classified into two classes as "*Judgement*": using or not-using self-service. "*CkinDensity*" is the number of passenger who finished check-in within 15 minutes timeframe. The actual number of passenger is classified into several classes ("*CkinDensity class*").

STEP-2: We conduct simulations by ABM multiple times to collect experimental results and form the other dataset. The dataset ("*dataset:ABM1*") has the variable "*hesitation*", "*ssubit*", and "*SPI*" and classified variable of "*turtle-density*". Table 4 describes what each variable stands for.

Table 4: Experimental Dataset

Variable	Value	Explanation
SSUflag	[0,1]	Actual result of self-service usage
CkinDensity	[0,1,2...n]	The number of checked-in passenger within unit-time (15 minutes) .
CkinDensity class	[0,1,2...n]	Classified congestion, the proxy function of lobby congestion
hesitation	[0-1]	Variable representing attitude towards self-service technology usage. It contains demographics, travel conditions, and heuristics including experiences and "technology anxiety".
ssubit	[0,1]	Result of self-service usage, which is produced from the ABM simulation
SPI	[-1,0,1]	Self-service preference index calculated through by the ABM
TurtleDensity class	[0,1,2...n]	Proxy function of congestion. The ABM counts the number of turtles(passenger) in the experimental space and those headcounts are classified into several classes.

STEP-3: We pick up the experimental data from *Dataset: ABM1* to form *Dataset:ABM2*, which are approximated to *Dataset:LR*, which has the same combination of passenger traits and congestion of departure lobby. Therefore, we have the same amount of data from two data sets, the data of those two datasets is similar to each other.

STEP-4: We aggregate each combination of passenger traits and congestion degree, calculate the true/false judgment of self-service usage prediction for each combination of two datasets, and compare the "*Correct-predict rate*" between them.

The "*Correct-predict rate*" of two spaces are to be examined whether the ABM works to increase prediction accuracy. "*Correct-predict rate*" is obtained as follows (eq.2, Fig.11).

$$Correct\_Predict\_rate = \frac{Passeger\_with\_correct\_predict}{All \quad passenger} \tag{2}$$

$$Predict \begin{cases} Correct & (SSUflag = Judgment) \\ Incorrect & (SSUflag \neq Judgment) \end{cases}$$

$$Predict \begin{cases} Correct & (SSUflag = ssubit) \\ Incorrect & (SSUflag \neq ssubit) \end{cases}$$

5.3 Evaluation and expextation

We compare "*Correct-predict rate*" which is the results of the four step procedure in 5.2. Guessing that difference between them comes from the behavior of an agent which move autonomously in the experimental space. We will discuss how the result of the interaction works for improving the accuracy of the prediction. Our expectation is to find the outcome of the experiment brings higher predict accuracy.

6 Conclusion

6.1 Summary

There have been much suggestive related work and many indications for SST adoption. We implemented the essence of related work into our ABM. In the service-marketing field, conceptual models supported by quantitative surveys indicate how attitudes formed and they lead to action. However, the results of statistic explain, but do not always demonstrate what an author means can be reproduced and how their mechanism actually functions.

This study illustrates and demonstrates how individuals opt for SST upon decision making by replicating the ABM model of self-service adoption at the airport. Data from an airline's system is used to explore the external and internal factors promoting SST. By examining boarding data, we find that heuristic factors explain whether to opt for SST more than travel conditions do. Recent self-service kiosk experience is the strongest factor to explain self-service kiosk usage in the dataset; higher flight frequency comes second. Even though herd behavior is observed at the service site, it is not significant statistically.

Since the simulation results through replicating the ABM remain close to the real data, this proves the expanded conceptual model with passenger traits reproduces the decision-making mechanism to a certain degree. The sensitivity analysis with the expanded ABM, SST adoption model, indicates deeper insights by examining the calibration of parameters. This study shows that ABM is capable of analyzing each component respectively, focusing on the process and simulating different situations and conditions of self-service adoption at the airport.

6.2 Subjects for future study

In this study, three categories of passenger were presented and implemented in the replicate model. Individual traits may expand the variance of experimental results, as mentioned in 4.3. Passengers could be divided into groups with proper proportions with more probability and we should consider to add some property given to each agent. Since structuring the dynamics of internal change of individuals is challenging, we need deeper aggregate analysis of individual traits before introducing the processed data into ABM.

The experiment in the previous work illustrates the influence for passenger's behavior by increasing the ratio of frequent self-service users with the SST adoption model. [14] In the real world the effort of lobby service staff raises the ratio of self-service usage. The scenario analysis with the SST adoption model observes that there is a threshold which the advantage of locating the lobby service staff no longer exists. In order to increase the number of frequent self-service users, it is also necessary to explore how the intention to reuse will increase. We need to know what kinds of success experiences of actual users will enhance the intention of reusing by exploring other research areas (e.g. user friendly man-machine interface, etc.).

There are many methodologies to analyze and explicate phenomena. ABM integrates other methodologies to construct a model framework. It is capable to pursue the behavior rule of an individual. And defined autonomous behaving rule can be used to explore the macro phenomenon.[13]

In chapter 5 of this study, we discussed the validating procedure of ABM to clarify its effectiveness. We should shortly work on this through the 4 step procedure, hoping that ABM simulation result will show whether it can enhance the explanatory capability of logistic regression analysis. Even though the real world is hard to be facsimiled completely, we need to continue to pursue the way to extract the essence of circumstances where our objective phenomenon occurs. We hope that those unsed data for the statistical model somehow is significant after those are processd by ABM.

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