The ASSA Project: An Intelligent Agent Simulation of Shop-Around Behavior

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Abstract. Policy exploration for downtown revitalization gets becoming important in also Japan. This article deals with a modeling and simulation project of downtown visitors' shop-around behavior using an intelligent agent approach, by mainly devising and implementing planning (dynamic scheduling/ rescheduling), learning and adaptation functions. In this article, first, we explain the architecture of ASSA model. Each agent makes and remakes his/her schedule to visit shops based on time constraints and shop preferences, chooses alternative visits when he/she fails in an errand, and makes impulse stops at shops and detour actions. ASSAver.3 was reported based on detailed observations and surveys taken at Asunal Kanayama shopping mall, and Osu shopping district, Nagoya. Then we show a framework of evaluation that included redundancy indicators for shop visits and walk lengths, and similarity analysis of shop-visit sequences. Valid-check results were shown in the simulation performances of the two cases of from these three aspects.

Keywords: Intelligent agent approach, Shop-around behavior, Planned action, Improvised action, Performance evaluation.

1 Introduction

In large modern cities, the behavior patterns of visitors to downtown have become increasingly diversified. For this reason, when we plan to promote a "lively" commercial district, it is important to analyze pedestrians' micro behavior, based on the bottom-up approach. In such an analysis, visitors' shop-around behavior within the commercial district is the primary focus on. It is clear that each pedestrian's shop-around behavior consists of multiple levels of activity; at first planned action in accordance with a pattern of preferences of the visitor, and later improvised action, such as the search for alternative shops or information acquisition. Furthermore, the behavior patterns of visitors are closely related to the agglomeration of shops and their spatial layout in a commercial district. Accordingly, development of a simulation model of pedestrian shop-around behavior in a commercial district can be a useful tool for analyzing the composition of a commercial district.

One of the major characteristics of pedestrian shop-around behavior is mix of premeditation and improvisation. That is, each pedestrian ranks the shops he/she will visit and plans a proposed route before the visit, whilst in the commercial district each of them will respond flexibly and change his/her plan according to the situation. In the construction of our shop-around behavior model, we considered it important to incorporate this key characteristic. Therefore, the ASSA model evolved into a non-Markov model and inevitably differed from the existing models that use the Markov chain[1]. Moreover, Agent-Based Social Simulation (ABSS) involving an autonomous individual with intelligence, was selected as the best technique to reproduce these behaviors ([2, 3]).

Taking into account the above the intelligent Agent Simulator of Shop-Around (ASSA) project was developed. We take a version-up development approach, ver.1, to include the functions of Planned Action and Improvised Action (Alternative Visit), ver.2, to include impulse visit, and ver.3, to include detour-type actions.

The most important element for checking the validity of such an intelligent agent model is the criteria used. To address this issue, a specific evaluation framework and indicators were devised in order to check the performance of several of the functional aspects of the model, and then to evaluate simulation performance through examples as illustrations and by comparing results with actual survey data, by applying the evaluation indicators. The performance results were examined from a variety of aspects and compared with features of actual visitors' demographics, preferences, behaviors and so on, both at Asunal Kanayama, a small shopping mall, and the Osu shopping street complex district in downtown Nagoya.

2 ASSA(Agent Simulation of Shop-Around) Project

2.1 Decomposition of Downtown Visitor's Shop-Around Behavior

The first feature of the downtown visitor's behavior that was modeled was the function of time allocation or scheduling of visits to shops under a limited time allowance (time-budget). Implementing the scheduling function in itself was an antithesis of the Markov model, even if it does emphasize time constraint, and was an application of the intelligent planning function in the agent. Shop-around behavior, as referred to here, has been explained in cognitive science [4]. The second feature was dealt with dynamic updates as part of the agent's behavior, including mainly rescheduling. This also relates to intellectual functions like adaptation and learning. Data-fitting oriented evaluation was the third feature of the agent behavior developed.

Next, the shop-around behavior to downtown Nagoya was investigated using 12 different survey results. As part of the survey, visitors were asked about the walking routes, shops visited, and whether the visits to the shops were planned in advance. According to the redundancy analysis (refer to 4.4), the shop-around behavior within a survey area, including the routes taken and the distance traveled, were found not to be necessarily optimized [5].

It was thus decided to decompose shop-around behavior into planned and improvised action. Improvised action was decomposed alternative-visit, impulse actions (Table 1). Planned action is an action performed according to a schedule. Alternative-visit action, which is defined as an improvised action, is the action of visiting a shop that was not part of the original plan because the planned errand was not completed in the shop visited [6]. This concept was not specifically differentiated in Markov-type shop-around behavior model

Table 1. Layer-decomposition of downtown visitor's shop-around behaviors.

Agent's Action		Information Processing		On Schedule Plan
		On Shop-Visit	On Path	
Planning & Decision Action		Planning a Visit-Order	Planning Path	Forming
Planned Action		Visiting Planned Shop in turn	Following Planned Path	Keeping
Improvised Action	Alternative-Visit Action	Choosing Same Category's Shop when Failed Errand	Modifying Path	Inserting
	Impulse Action	Impulse-Visit (Stop) Action: Dropping in Non-Planned Shop if Time Available	Impulse-Detour Action: Walking Non-Shortest Path if Time Available	Re-forming

2.2 Features of Three Versions of ASSA

The focus is mainly on the Shop-Around Submodel (Fig. 1).

Features of ASSAver.1 and ver.2. ASSAver.1 deals only with Planned Actions and Alternative Actions (task completion / failure is represented as a fixed probability for each errand). The rescheduling function was developed in the case of a failure to complete an errand. Moreover, the tight assumption Presupposes that all of the 'path planning' is always optimized by Dijkstra method.

In ASSAver.2, Impulse Visit Action is defined as "an impromptu visit to a shop in the commercial district that is neither a Planned Action nor an Alternative Visit Action." Impulse Visit expresses the completely spontaneous behavior of an agent. Each impulse visit action is determined probabilistically when visiting each street, based on street appeal, shop preference and time remaining by the e-greedy method (for much details, see[6, 7, 8, 9]).

Fig. 1. Basic behavior of downtown visitor agent in ASSA

Features of ASSAver.3. ASSAver.3 adds two kinds of Detour Actions: one is the relaxation of the optimality of path planning, and the other is about taking a detour on Impulse. Several studies had appeared such as [10], but no study deals with the time-constraint.

Detour at the Plan Making Action. As mentioned previously, detour behavior at the planning stage occurs during route planning. Therefore, we have removed the optimality assumption of path planning in ASSAver.1. The relaxation means that the visitor deliberately selects a longer route, even though the visitor knows the shortest route, based on considerations such as safety, degree of congestion, or preference toward particular streets. In order to implement the above behavior in the model, we weighted each agent relative to each link in the network of commercial districts. With this weight applied, each agent would select a psychologically or emotionally shortest route as opposed to the physically shortest route. Therefore, even though agents themselves believe that they planned to take the shortest routes, the actual routes planned would be the longer routes at the planning action stage. The weight applied to each link was determined by adding a randomization item to preference values against the facilities possessed by each agent.

Impulse-Detour Action. Impulse-detour action is positioned opposite to improvisation. It is a planned route departure behavior, which is a higher-order function. The softmax method that uses Boltzmann distribution was used to model this behavior. The steps are as follows. First, when visiting a commercial district, locations that are different from the original destination are selected at random. Next, the values of the selected locations are calculated based on the distance between the current location and the selected locations, and the weight of each location (the weight for each selected location is the same as that given in the Detour at Plan-Making Action stage). Based on these values, the probability of selecting each location is determined using Boltzmann method. Note that we have decided that impulsive detour behavior will not occur if β is less than 0.1 [6].

3 Evaluation Framework and Performance Measurements

In this paper, from the standpoint of a 'constructive modeling', we adopted a traditional dichotomy in urban simulation fields; system verification and model validation.

System verification is used as the completeness of coding intuitively, or 'No Bug proof'. Agent simulators also got become complicated as computer softwares, so in such cases, software development framework should be applicable.

Model validation consists of two parts at least; (1) the soundness of model 'structural' formulation in comparison with the nature of a problem entity, and (2) the goodness of data-fittings of major parameters in the designed model. Model validation affects mainly forecastability or explainability of the simulation results. Although the former model structures are created through insightful observation, calibration process is mainly required at the latter phase.

Here, considering the characteristics of an 'intelligent agent approach' that differs the existing LLPM type microsimulation, in this paper we proposed a new evaluation framework of the simulation performance. (3) illustration of individual agent's behavior is closely concerning to the system validation, otherwise (1) and (2) are for the common basics of the model validation, and (4) and (5) deal with the model validation as intelligent agent.

3.1 Evaluation Focus

To evaluate the characteristics of the above designed model, simulation were analyzed taking into account the following five points.

General evaluation.
(1) Analysis of aggregated behavior (for basic model validation)
(2) Analysis of statistics (for basic model validation)
Individual function evaluation.
(3) Illustration of agent's individual behavior (for system verification as intelligent agent)
(4) Analysis of similarity of visit sequence (for model validation as intelligent agent)

(5) Analysis of redundancy (for model validation as intelligent agent)

3.2 Analysis of Similarity in Visit Sequences

Shop-visiting behavior patterns for each sample from the simulation and the survey observations were compared so as to check a validity how closely the following elements resemble each other: the shops visited, visiting order, and the number of shops visited ([11] as an existing approach).

For this valid-check, the concept of Levenshtein distance was introduced. To be specific, an agent sample and survey sample were assorted to correspond one-to-one, from among the visit sequences, and the Levenshtein distance was calculated by assigning a cost of 1 for each insertion, deletion and substitution, and this result was used to assess to what extent agent’s behavior reproduced shop visits by a real pedestrian. To match the visit sequence of a particular agent, we selected survey samples of the same gender and age category, and from among them, the survey sample whose Levenshtein distance was the shortest was used. The average and variance of the shortest Levenshtein distances as a whole were obtained to conduct variance analysis. In addition, the percentage of sample pairs with a Levenshtein distance of 0--meaning the visit sequences are identical--was also used as an indicator.

It is important to note that the Levenshtein distance is determined based on the one-to-one correspondence of the results for a simulation sample with a survey sample; therefore, the average and variance of the Levenshtein distance for the whole sample changed according to the correspondence determination method.

Consequently, to maintain the validity of this indicator, a method of setting an objectively acknowledged optimum sample pair must be adopted. It was decided to consider the problem as applicable to a stable marriage. Regarding “a man” in this problem as an agent sample, “a woman” as a survey sample, and the “ranking” as the Levenshtein distance from the marriage partner, by matching stable agents with stable survey samples, it was possible to find the optimum sample pair. However, there is a plurality of solutions for stable coupling; therefore, a plurality of solutions was calculated by changing the permutation of samples, and a solution that gave the minimum average value of the shortest Levenshtein distance was adopted. (For examining the performances, we employed the average value of twenties calculations)

Displayed equations or formulas are centered and set on a separate line (with an extra line or halfline space above and below). Displayed expressions should be numbered for reference. The numbers should be consecutive within each section or within the contribution, with numbers enclosed in parentheses and set on the right margin.

3.3 Redundancy Analysis of Walk Length

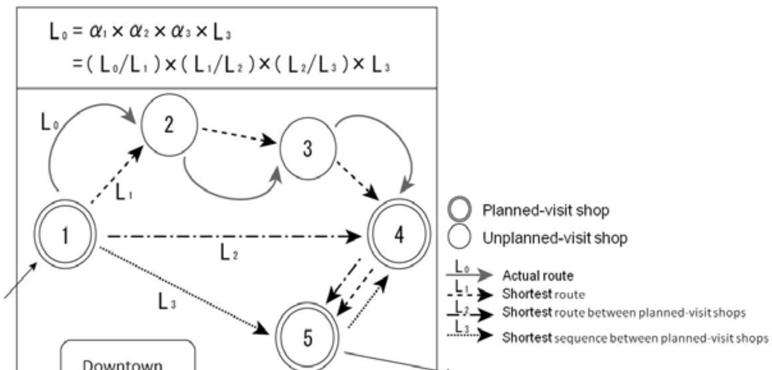
In both the simulation and survey attention was paid to the degree of behavior and the scheduled plan deviate from the optimum geographical distance solution, and by comparing them, the behavior and planning characteristics of the model were validated. The similarity analysis of visit sequences in the previous section paid attention to visiting order and examined the degree of similarity between samples, whereas this analysis focuses on geographical distance and compared the degree of deviation from the optimum route distance. For checking the validity, detour behavior indicators consisting of the following three levels were adopted, as proposed by [5] (see also Fig. 2).

Level 1 indicator. This indicator expresses the degree of deviation from the shortest distance between shops, the difference between the actual distance walked between shops and the shortest distance between shops. This indicates redundancy with regard to the route between shops and can be interpreted as a detour.

Level 2 indicator. When the shortest distance (route) between a shop planned to be visited (hereinafter planned-visit shop) and the next planned-visit shop is regarded as a benchmark, this indicator represents the degree to which the shortest route between the shops actually visited deviates. This indicates redundancy, such as an unplanned visit, and when this value is high, it can be interpreted as behavior that had been extended to include unplanned visits to shops some distance away, for example, to run a new errand within the district.

Level 3 indicator. When the distance (route) between planned-visit shops of the shortest sequence is regarded as the benchmark, this indicator shows the degree to which the shortest route between the planned-visit shops deviates of the actual visit sequence. This indicates redundancy concerning a plan for the shops visit sequence, and can be interpreted to mean that the lower the value, the more efficient the sequence taken.

By showing a hierarchical decomposition of pedestrian behavior in Table 1, these indicators can be reinterpreted as follows: the Level 1 indicator shows how often a detour from the planned route occurs in the Impulse-Detour Action; the Level 2 indicator shows how often impulsive visits occur in the Impulse-Visit Action, and how often alternative visits and route revision occur in the Alternative-Visit Action; the Level 3 indicator shows the degree of deviation between the plan made by a pedestrian at the Planning Action stage and the optimal solution. Accordingly, a comparison of the results of agent behavior with those of survey samples using these indicators allows us to verify the following: characteristics of detours from the planned route (Level 1 indicator); characteristics of impulsive and/or alternative visits (Level 2 indicator); the efficiency of a plan (Level 3 indicator).



(Alpha1: Level 1 indicator, Alpha2: Level 2, Alpha3: Level 3)

Fig. 2. Explanation diagram of redundancy indicators.

4 Evaluation of Simulation Performance

By employing ASSA as the simulation model we conducted simulation experiments and evaluated the experiments using the evaluation framework. The following two cases in Nagoya were applied: Asunal Kanayama, a three-storied shopping mall with 60 shops divide into 4 categories (28 commodity stores, 15 cafes and restaurants, 15 services and 2 wagons); and Osu district, a shopping street complex district with 685 shops falling into 8 categories (cafes and restaurants, grocers, household goods, electric appliances, clothing, parks and temples, second hands goods, and others). The latter is modeled as a network with 36 street-nodes. Detailed survey data for both cases had already been obtained. ([12],[13]). Visitors were categorized by 2 genders , 3 age groups and other attributes such as location of domicile and visit frequency.

In the Kanayama Simulation Case, performances of 3,000 agents during 120 holidays were recorded and founded to be stable after the trial 30 holidays, so the average of these was used. In the Osu Simulation Case, 2,500 agents' during 120 days were recorded, after the trial 10 holidays, were used.

4.1 Overall Performance of ASSA

Table 2 shows comparisons between survey data and the simulation results obtained using ASSAver.1, 2 and 3. Please note that the simulators used time distance expression, whereas the actual physical distance traveled was extracted from the route drawn on the maps of the surveys, making comparison between the two impossible. Therefore, the distance traveled is shown only for reference. Free walking speed is generally said to be between 1.2 m/s and 1.5 m/s. If the simulation data is converted into distance using these values, the distances traveled fall in the range of 172 m-216 m, 65 m-81 m, and 238 m- 297 m for ASSAver.1, 2 and 3, respectively. Comparing other values, it is evident that the duration of a visit to commercial district is shorter by approximately 14 minutes and the numbers of facilities visited is about 0.7 facilities fewer for ASSAver.3 compared with the survey data. The simulations showed realistic values for planned facility visits.

Table 2. Aggregated results for ASSAver.1,2 & 3 in the Kanayama Simulation Case.

	ASSAver.1	ASSAver.2	ASSAver.3	Survey
Ave. Stay Time (min.)	54	70	80	94
Ave. Walk Time (m) /time (min.)	2.4min	0.9min	3.3min	147m
Ave. # of Visited Shops	1.07	1.85	2.11	2.84
Ave. # of Planned-Visit Shops	0.74	0.71	0.61	0.63

Osu Simulation Case. Here, we examine one agent behavior in the Osu Simulation Case whose behavior was of particular note (Fig. 3). The agent was a <young woman> sample who came from <middle-distance> by <train>. From her plan, it can be see that she intends to visit five shops: clothing shops <A>, <B>, <C>, <D> and an electric appliance shop <E>.

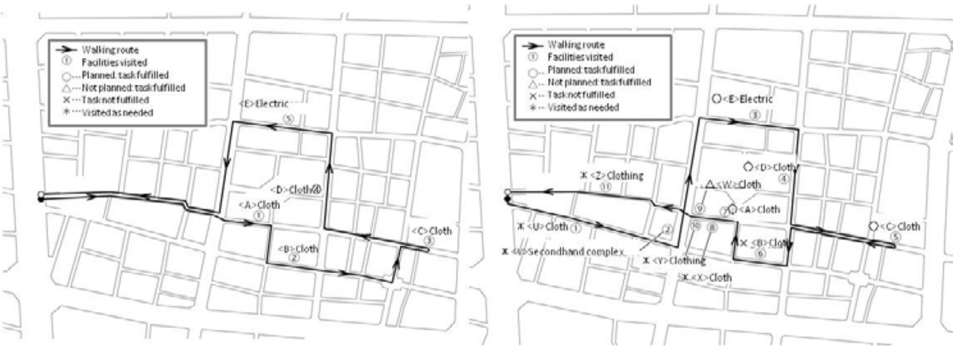


Fig. 3. An Agent's behavior in Osu Case (Left: plan, Right: performance)

Once this agent arrived in the district, she actually first visited a different clothing shop <U> (1). The agent walked by way of a street that is not the shortest route to shop <A>, the first planned-visit shop; therefore, it can be seen that the detour behavior function was working. Next, the agent visited a secondhand goods shop <V> (2), which again was not included in the plan, and as a result of these unplanned visits, the agent changed her plan yet again and went to shop <E> (3), which she had planned to visit at the very end of her trip. In the three shops (3) and the subsequently visited <D> (4) and <C> (5) -- the agent successfully fulfilled all her errands, but in <B> (6), she failed to complete her errand. As an alternative shop she chose <W> (9). But before visiting <W> (9), she visited <A> (7), which she had planned to visit earlier, and then made an unplanned visit to another clothing shop <X> (8). In <W> (9) the agent completed the errand that she had failed to do at <B> (6), and then made unplanned visits to yet more clothing shops <Y> (10) and <Z> (11), and finally went home. From these observed results, it is evident that each Agent Action shown in Table 1 was working in a complex way. In addition, the Impulsive-Visit Action of visiting several

clothing shops in sequence is characteristic of the young women who actually visit this commercial district; from this point; confirms that the model is capable of rescheduling a set of behaviors unique to agents' attribute.

Kanayama Simulation Case. Fig. 4 (a) and (b) show the results of aggregated behavior analysis with a focus on pedestrian passage percentage distribution. With regard to the ground floor of the Kanayama mall, it is apparent that the simulation results almost match the survey data. On the 2nd and 3rd floors, the simulation shows fewer visits than the survey. To remedy this the following can be done: weaken the negative effect of distance when shops are selected; to improve parameters for the preference of shops and streets; adjust the negative effect of visiting higher levels in multistory shops.

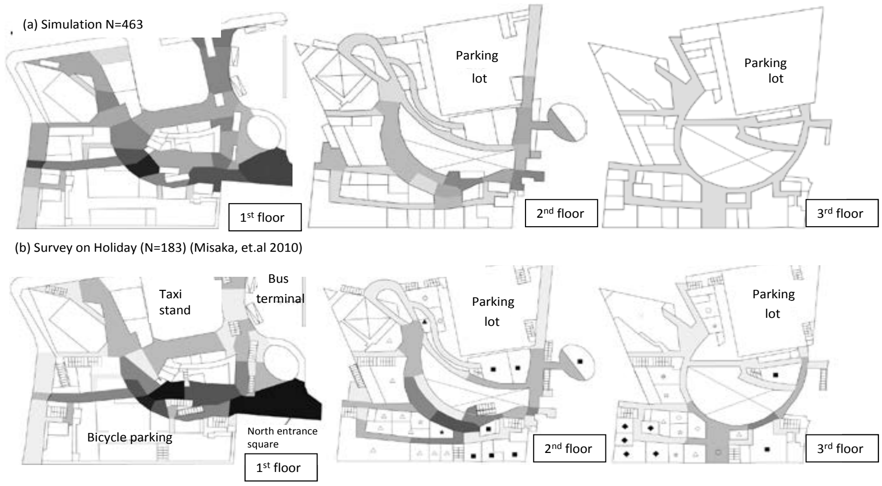


Fig. 4. Pedestrian spatial distributions in Kanayama Simulation Case

4.2 Individual Function Evaluation: Kanayama Simulation Case

Table 3 shows the verification results for visit sequence similarities. The average value and standard deviation value of the shortest match pairs in terms of Levenshtein distance between all the sequences in the results of the 30 times runs (hereinafter, the shortest LD) were 2.03 and 1.96, respectively. This means that when one sample each is selected at random from the simulation and the survey, the number of steps require to produce identical visit sequences is 2.03 times on average. In addition, the percentage of completely matched samples whose visit sequences were identical accounted for 22.09% of all the sequences (hereinafter, referred to as the EM ratio). When the results were examined according to agents' attributes (demographic groups), older men showed the highest evaluation for the shortest LD average value. This indicates that agents in this category had a good average similarity within the category. Evaluation in terms of the EM ratio, found <middle-aged men> had the highest percentage, which indicates that agents in this category were the best at completely reproducing the visit sequence within the category. Compared to women agents, men agents of all ages achieved high similarity with the survey; when the results were examined according to age group, the younger age groups tended to have lower degrees of similarity compared to other age groups. Women account for the majority of visitors to Asunal Kanayama shopping mall; therefore, with regard to this demographic further improvement in similarity is needed.

Table 3. Results of similarity analysis of visit sequences in Kanayama Simulation Case

	Number of samples		Average of the shortest LD	Standard deviation of the shortest LD	EM ratio (%)	Test
	Total	249	2.03	1.96	22.09	NE
Gender	Men	57	1.67	1.56	28.07	*
	Women	192	2.14	2.08	20.31	
Age	Younger	54	2.65	2.24	14.81	*
	Middle age	129	1.83	1.74	20.16	
	Older	66	1.92	2.14	31.82	
Six attributes	Younger: Men	11	2.00	1.91	9.09	NE
	Younger: Women	43	2.81	2.26	16.28	
	Middle age: Men	27	1.74	1.48	33.33	
	Middle age: Women	102	1.85	1.79	16.67	
	Older: Men	19	1.37	1.35	31.58	
	Older: Women	47	2.15	2.32	31.19	

4.3 Redundancy Analysis: Kanayama Simulation Case

Table 4 shows the results of the redundancy analysis. Under the Level 1 indicator, the simulation showed higher values for Group 3, with agents tending to take more detours than found in the survey. Under the Level 2 indicator, compared to the survey, the simulation results showed higher values for Group 1; and, compared to the survey, the simulation showed less evidence of Impulse-Visit and Alternative Actions. Moreover, when the number of planned-visit shops were examined and compared with the survey, the simulation results showed a large difference in the occurrence of Improvised Action. Under the Level 3 indicator, because of the small number of survey samples, only the simulation result was analyzed; however, it was possible to confirm the efficiency of the plan made by an agent, and that the rescheduling of planned actions due to the occurrence of Improvised Action was affected by the number of shops visited and the number of planned-visit shops, whereas it was not affected by gender, age, and frequency.

Table 4. Results of redundancy analysis for the Kanayama Simulation Case

		Simulation					Survey				
Level 1 indicator		N(people)	Group1	Group 2	Group3		N(people)	Group 1	Group 2	Group3	
		575	243	131	201		111	38	40	33	*
Number of planned-visit facilities	0	181	45	37	99	**	62	18	21	23	
	1 or more	394	198	94	102		49	20	19	10	
Number of facilities visited	0 or 1	279	132	37	110	**	46	16	11	19	*
	2 or more	296	111	94	91		65	22	29	14	
Frequency of visit (per week)	1 or more	457	180	108	169	*	50	20	17	13	
	Less than 1	118	63	23	32		61	18	23	20	
Duration of stay (minutes)	Up to 30	124	36	19	69		33	11	9	13	
	Less than 120	158	64	46	48	**	39	16	12	11	
	120 or more	293	143	66	84		39	11	19	9	
Level 2 indicator		N(people)	Group1	Group 2	Group3		N(people)	Group 1	Group 2	Group3	
		575	278	151	146		111	33	34	44	**
Gender	Men	165	96	29	40	**	18	6	5	7	
	Women	410	182	122	106		93	27	29	37	
Number of planned-visit facilities	0	181	63	32	86	**	62	15	15	32	**
	1 or more	394	215	119	60		49	18	19	12	
Number of facilities visited	0 or 1	279	245	17	17	**	46	26	12	8	**
	2 or more	296	33	134	129		65	7	22	36	
Frequency of visit (per week)	1 or more	457	223	121	103	**	50	19	16	15	
	Less than 1	118	45	30	43		61	14	18	29	
Duration of stay	Up to 30	124	81	17	26		33	16	8	9	
	Less than 120	158	75	34	49	**	39	8	14	17	
	120 or more	293	122	100	71		39	9	12	18	
Level 3 indicator		N(people)	Group1	Group 2	Group3		N(people)	Group 1	Group 2	Group3	
		394	209	54	131		49	33	9	7	*
Gender	Men	118	66	10	42		Due to the small number of samples, testing was not possible.				
	Women	276	143	44	89						
Age	29 or younger	128	62	22	44						
	30 to 49	135	78	15	42						
	50 or older	131	69	17	45						
Number of planned-visit facilities	1	333	200	35	98	**					
	2 or more	61	9	19	33						
Number of facilities visited	0 or 1	185	120	13	52	**					
	2 or more	209	89	41	79						
Frequency of visit (per week)	1 or more	326	170	43	113						
	Less than 1	68	45	11	18						
Duration of stay	Less than 120	134	77	14	33						
	120 or more	260	132	40	88						

**5% significant difference *10%significant difference

5 Conclusion

In this article, features of ASSA (Agent Simulation of Shop-Around behavior) project were demonstrated, and particular attention was paid to performance evaluations from several aspects of the proposed shop-around pedestrian agent. The key element included in the ASSA model is the improvisational character of the downtown visitor's behavior under time-budget constraints, as opposed to the existing Markov-type models, emphasized transition probabilities between visits inside the district. It needs that a new kind of performance framework and criteria were required, which included visit-sequence similarity and multi-level walk-length redundancy as well as full illustrations of these. The results of the simulations suggest the potential of the ASSA model to simulate the "naturalistic and intelligent" shop-around visitor's behavior, although some fine-tuning of the parameters still remains as well as developing a 'tune-up' technique.

In ASSA project case, some of calibrations are 'trivial', because the parts of the model structure is devised on the results of data analyses, the others are still 'ad hoc'.

After proposing an evaluation framework, we show this potential through illustrating digests of these measurements.

The following issues are those that future studies can address: the further improvement of the usefulness of the model based on this study; the further development and reconstruction of the evaluation framework; and the further development issues include efficient parameter-fittings though the relationships of the parameters are complicated.

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