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A HEURISTIC-BASED AIRPORT SHOPPING BEHAVIOR MODEL WITH AGENT-BASED SIMULATION

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ABSTRACT

In recent years, the source of airport revenue has significantly changed. Accordingly, many airports have adjusted their strategies and focused on increasing retail revenue to improve financial sustainability. However, there is a lack of application of shopping behavior models to airport retail development. This paper aims to fill this gap by presenting a heuristic-based shopping behavior model. First, this paper briefly reviews the existing literature on heuristics for modelling shopping behavior. Second, research data collected at a case study airport is used to calibrate and validate the proposed agent-based simulation model. The Mean Absolute Percentage Error of the model stands at 5.3% on total footfall across all retail shops. The validation result demonstrates the feasibility of the proposed model in simulating the heuristic used by shoppers in airport retail. The proposed model provides an excellent foundation for future scenario studies on airport retail.

1 INTRODUCTION

Airport retail revenue is a critical component of the non-aeronautical airport revenue. It is estimated that airport retail revenue reached US$ 39.4 billion globally in 2020 and is set to grow at a compound annual growth rate of 7.2% to reach US$ 64.2 billion by 2027 (Analysts 2021). Airport retail revenue is the single largest source (30.2%) of the non-aeronautical revenue as demonstrated in Figure 1. Airport retail has benefited greatly from the increase in passenger volume and the liberalization of the aviation industry. The liberalization and deregulation forced airports to look into alternate sources of revenue to replace the aeronautical revenue due to the increasing market power of airlines (Fuerst and Gross 2018).

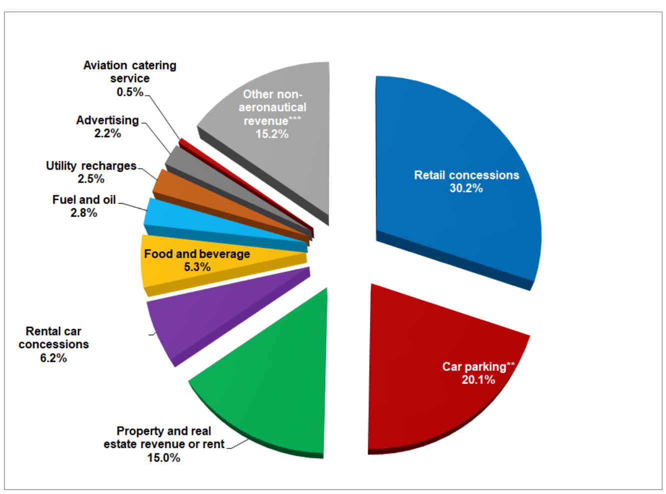

Figure 1: Worldwide airport non-aeronautical income breakdown by source for 2017 (ACI 2019).

Airport retailers should always consider how their sales offer resonates with the primary activity (to fly) the crowd is pursuing. While airport retailers have learned to locate their retail facilities in the direct line of passenger flow, the positive effect of this is often offset by the ‘bigger is better' design philosophy of the airport terminal (Doganis 2005). The bigger the airport terminal, the more challenging it is to ensure these retail facilities are in the direct line of passenger flow. Airport retailers have learned and applied the idea of ‘comparison shopping' in the airport shopping environment (Kim and Shin 2001). The exchange of ideas between the shopping center management and the airport retail industry shows that it is worthwhile for airport retail operators to learn from similar industries.

Kalakou and Moura (2014) noted that an airport pedestrian behavior model would give airport operators a better understanding of how passengers with different characteristics perceive the airport space and move around in the terminal. However, a study by Choi et al. (2016) found that airport retail research only accounts for 5.3% of shopping tourism research. Furthermore, airport retail research has not benefited from general consumer shopping behavior models (such as pedestrian behavior models) to a large extent (Chen et al. 2020; Creed et al. 2021). A similar pedestrian behavior model approach can be suitably applied in the airport context. However, Lee et al. (2021) pointed out that airport passenger shopping behavior differs from the traditional retail store environment. Therefore, before implementing any pedestrian behavior models in an airport context, it is vital to understand airport passenger shopping behavior.

This research addresses the research gap given the lack of a shopping behavior model in the airport context. This paper presents a brief literature review on pedestrian shopping behavior in the broad retail context, focusing on exploring the heuristics that shoppers may adopt. In this study, we model passengers who use heuristics to make shop visit choices. The paper is organized as follows. Section 2 presents brief literature on the passenger shopping behavior model. Section 3 discusses the data collection process. The development of a heuristic-based shopping behavior model is explained in Section 4. Section 5 discusses the verification, calibration, and validation of the heuristic-based model in a simulation setting. Section 6 concludes the findings and discusses the implications.

2 LITERATURE REVIEW

Van Middelkoop et al. (2003) defined heuristics as a rule that connects the outcomes of a choice decision, in either a deterministic or probabilistic way, to the description of a particular choice situation. Passengers may not always make the most optimal decisions and they may accept a satisfactory alternative decision.

Van Der Hagen et al. (1991) showed that the distance-minimizing strategy is only one of several potential decision heuristics pedestrians could apply. Local-distance-minimizing (LDM) heuristics implies that pedestrians would attempt to take the shortest route between successive shops on a shopping trip (Van Der Hagen et al. 1991). Total-distance minimizing (TDM) assumes that pedestrians would minimize the total distance in their route choice (Van Der Hagen et al. 1991). Kurose et al. (2001) also pointed out that TDM can be derived from utility maximization choice theory. Global-distance-minimizing (GDM) heuristics means that pedestrians might still visit the store in an optimal order, without minimizing the total distance (Van Der Hagen et al. 1991). Kurose et al. (2009) analyzed pedestrian behavior with heuristics and found pedestrians not applying the LDM, TDM or GDM make more back-tracking.

Timmermans and Van der Waerden (1992) further outlined that pedestrian may implement different decision heuristics. Accordingly, spatiotemporal sequencing of activities become more complex as the length of trip and the number of stop increases. Timmermans et al. (1992) provided a comprehensive review of pedestrian movement models and found that a pedestrian might apply a sequential decision-making process and minimize the distance travelled if the pedestrian has a pre-selected set of destinations to visit. Kurose et al. (2001) presented a rule-based system of choice heuristics to categorize shopping behavior and demonstrated effectiveness in the model in classifying pedestrian behavior.

Van Middelkoop et al. (2003) argued that tourists do not exhibit utility maximization in selecting a travel mode, and their choice behavior is context-driven. Van Middelkoop et al. (2003) used a decision table to represent choice rules and a CHAID-based algorithm to successfully derive these choice rules from empirical data. Van Middelkoop et al. (2007) further demonstrated the feasibility of using the decision table in analyzing consumer decision-making process and effectively formalized choice heuristics through the decision table. Zacharias et al. (2005) used four simple heuristics in replicating the movements of a pedestrian in a shopping mall, including: (1) random walk; (2) distance-limited walk; (3) connectivity walk; and (4) goal-directed walk in a shopping center simulation. The results from the study by Zacharias et al. (2005) show that random behavior is not a useful heuristic rule for describing actual shopper behavior and goal-directed behavior best describes shopper spatial behavior.

Zhu and Timmermans (2006) pointed out that most pedestrian behavior research in general retail has predominantly focused on utility maximization models and neglected other behavioral theories such as bounded rationality. According to Sent (2005), the concept of bounded rationality 'started from the rationality assumption' but assumes that consumers are bounded by their limitations. Zhu and Timmermans (2006) argued that more realistic models might be built on bounded rationality theory. Zhu (2008)'s thesis provided an extensive literature review on pedestrian shopping behavior models and tested the application of heuristics models on shopping behavior with the principle of bounded rationality.

Based on the work by Zhu (2008), Zhu and Timmermans (2010) presented three typical heuristics for decision modeling, namely the conjunctive, disjunctive, and lexicographic rules. *Conjunctive rule* means that a choice alternative will only be satisfactory if it meets a set of attribute thresholds. *Disjunctive rule* means that an alternative will be satisfactory if it has at least one attribute higher than the corresponding threshold. *Lexicographic rule* assumes that two alternatives are compared on an attribute-by-attribute basis following some factor search sequence organized by descending ranking of factor importance (Zhu and Timmermans 2010). Zhu and Timmermans (2011) proposed a shopping behavior modeling framework with bounded rationality and a multi-agent simulation. Their result showed that heuristic models performed slightly better than multinomial logit models in simulating spatio-temporal agent behavior. Zhu and Timmermans (2011) found that individuals often use simple heuristics based on bounded rationality to reduce the cognitive burden and make non-optimal, satisficing choices.

3 DATA COLLECTION

3.1 Data Collection Context

Two data collection exercises were designed for this research to collect the required research data. Given that movement data is paramount to developing the model, a mobile eye tracker was used to record and observe passenger movements and overcome memory recollection issues. Using the mobile eye tracker would provide rich information from a first-person perspective of the passenger. This qualitative study would deepen the understanding of passenger movements and shopping behavior within the airport terminal. While the first part of data collection is more qualitative in focus, the second part is quantitative. It aimed to increase the sample size and validate various concepts within the literature and the results from the qualitative study. Both data collection exercises were conducted in January 2019 in an international airport based in Asia.

3.2 Participants

Forty passengers (21 male, 19 female) were recruited randomly to participate in the qualitative data collection (eye-tracking data). Three samples were excluded due to the technical issues when using the eye tracking device. Another three samples were excluded as passengers did not arrive at the gate early enough before the boarding time to complete a follow-up interview. Only 34 of the participants completed the full exploratory study (with the use of eye-tracker).

A random sample of 300 participants (167 male and 133 female) was recruited to complete the quantitative data collection. A valid sample comprises questionnaire data and a semi-structured interview discussion. Therefore, only 280 participants completed the entire data collection exercise, and their results were considered valid.

3.3 Procedure

There were two stages of data collection for the qualitative study. In the first stage, participants were approached and asked to participate in the study. Once the participants agreed, they completed the first questionnaire section. Next, the researcher fitted the mobile eye tracker on the participants and prepared for pre-offline calibration. After the researchers completed the pre-offline calibration process, participants could participate in their activities as per usual while wearing the eye-tracking device. The participants were not given instructions to complete any specific activities, nor were they physically followed during their time in the airport terminal. After participants reached the boarding gate, they returned the eye tracker and completed the second part of the questionnaire. For the quantitative data collection, the data collection procedure was almost identical to the data collection procedure in the eye-tracking study. However, the mobile eye-tracker was not used in the second data collection exercise.

3.4 Data Analysis

Based on the qualitative and quantitative data collection, participants primarily exhibited four types of behavior when planning their retail-related activities in the airside of an airport terminal (i.e. the areas after immigration/border control): gravity-based (unplanned shopper), heuristic-based (partially planned shopper), scheduled-based (completely planned shopper), and apathetic shopper (non-shopper). In this paper, the primary focus is the heuristic-based shopping behavior. Table 1 outlines the profile of passengers with heuristic shopping behavior. During the qualitative study, 10 or 29.4% of the 34 participants are identified as heuristic shoppers. During the quantitative study, 73 or 26.1% of the 280 participants relied on heuristics for their shopping strategy. The quantitative data collection confirmed the presence of heuristic shoppers in the airport context as both studies showed a close approximation of the percentage of heuristic shoppers among the air passenger population. This study only focused on the heuristic-based shoppers; hence, these 83 samples are used for subsequent modeling of heuristic-based shoppers.

Table 1: Heuristic-based shoppers' profile.

Data collection	Number/percentage	Gender	Travel Purpose
Qualitative data collection	10/29.4%	Male (6), Female (4),	Business (4), Leisure (6)
Quantitative data collection	73/26.1%	Male (39), Female (34),	Business (51), Leisure (22)

4 MODELLING RETAIL SHOPPING HEURISTICS WITH AGENT-BASED SIMULATION

In this study, we model passengers who use heuristics to make shop visit choices. We adopted the bounded rationality principle to model this heuristic-based shopping behavior. Despite having a shopping plan and preferred shops in mind, these passengers often decided to visit different shops when they did not see the shops that they originally planned to visit. These passengers made a series of decisions based on the limited information available while they walk across the terminal towards the boarding gate. They simplified their decision-making with heuristic rules and tried to find a solution that was reasonable; that is, passengers would visit a shop that was not initially planned and chose to visit the most attractive shop based on limited information. In particular, the heuristic shoppers' decision-making was modelled by a staged decision-making process, which is both guided heavily by heuristic rules and, to a smaller extent, utility maximization principles.

4.1 The Decision-making Process

Figure 2 outlines the proposed decision-making process model of a heuristic shopper. In this model, a heuristic shopper moves into the airside shopping area after passing through immigration and security checks. First, passengers are guided by heuristic rules to decide on the direction of movement. Passengers will only decide to stay in the shopping area if there is enough time to do so (according to time heuristics). If passengers stay in the shopping area, passengers will check the surroundings within their visual distance (according to distance heuristics). Since heuristic shoppers have already planned to visit specific shops, these shops exhibit the highest attraction levels for these passengers. Therefore, if the target shops appear in the initial visual search, they will be visited first, depending on whether the shop is overcrowded. If the visible shops were not included in the passengers' original plan, they will choose another shop with the highest attraction level or they might decide to move on. After each shop visit, there is a reduced chance of revisiting the same shop immediately.

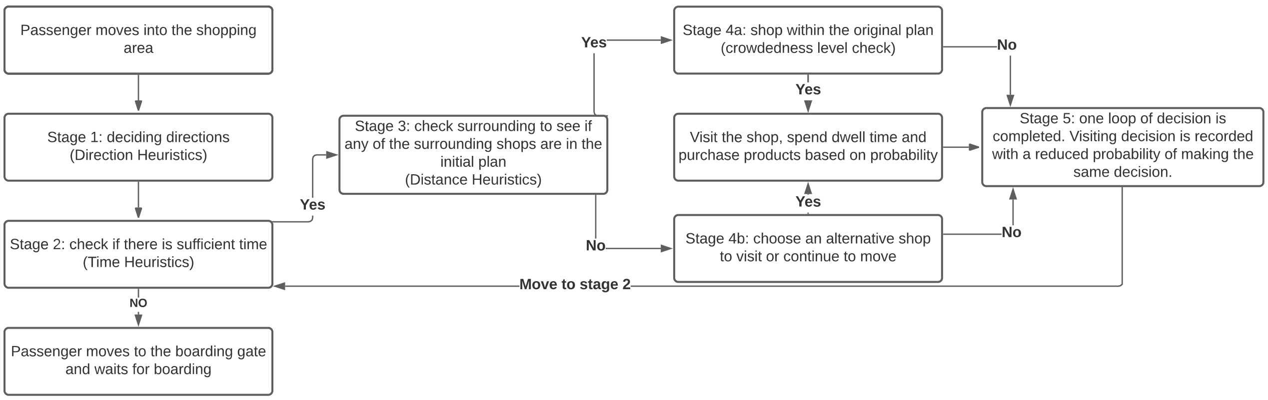

Figure 2: The decision-making process of heuristic-based shoppers.

4.1.1 Direction Heuristics

The critical assumption in direction heuristics is that passengers gradually move in the direction of their boarding gate. It is incredibly challenging to entice passengers to move away from the boarding gate once they have reached the boarding gate. This behavior is also known as the 'gate lock' in the airport retail context (Freathy and O'Connell 1998; Livingstone 2014). In the simulation, once the passenger arrives at the boarding gate, the simulation is considered complete for this passenger and there would be no further retail activities for the passenger.

4.1.2 Time Heuristics

Time heuristics assume that passengers are aware of their boarding time; once they move into the boarding gate area, they tend to remain there until they board their flights. Time heuristics also assume that longer dwell time available to a passenger will increase the likelihood of staying in the shopping area. If passengers have not arrived at the boarding gate, it is assumed that they remain in the retail area and are possibly conducting discretionary activities including retail shopping.

The questionnaire recorded the remaining dwell time of participants when they reached the boarding gate. This data was used to empirically derive the probability distribution of passengers arriving at the boarding gate as a function of the remaining dwell time. Hence, the probability of passengers arriving at the boarding gate with t minutes remaining dwell time, denoted by p_t, can be empirically calculated by the following equation (1):

$$p_t = \frac{n_t}{\mathrm{N}}, \tag{1}$$

where t is measured by 15-minute intervals before the scheduled departure time; n_t is the number of passengers arriving at the boarding gate in time interval t; and N is the total sample size of the questionnaire.

It is assumed that if passengers are not at the boarding gate waiting for boarding, then they must still be in the retail area of the terminal, and thus have a likelihood of visiting shops. Hence, the probability of a passenger remaining in the retail section in time interval t, denoted by s_t, is the inverse of p_t according to equation (2):

$$s_t = 1 - p_t. \qquad (2)$$

Accordingly, the probability of a passenger remaining in the retail section with the remaining dwell time longer than t is expressed as the cumulative density function (CDF) of s_t, denoted by S_t where $S_t = \sum_t s_t$. The results of this CDF (S_t) were calculated from the questionnaire data and are shown in Figure 3.

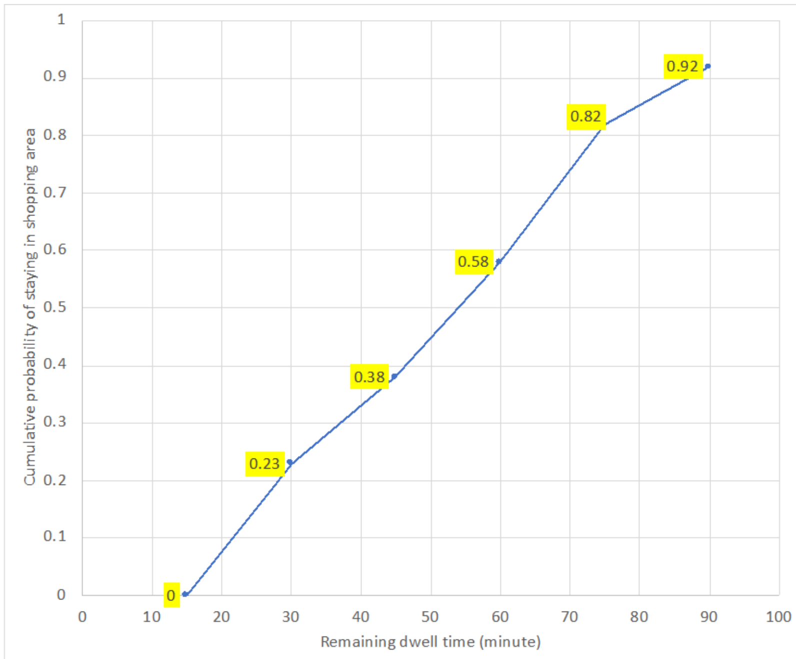

Figure 3: Cumulative probability of passengers staying in the shopping area.

4.1.3 Distance Heuristics

There are two components in the distance heuristics. First, heuristic shoppers' decision-making is restricted by their visual distance. It was estimated that passengers' visual distance was 10–25 meters based on the eye-tracking study. This estimate was affected by various crowdedness levels in retail shops, and individual eyesight conditions of participants. The second assumption of the distance heuristic is that a passenger's distance from a particular shop is assumed to be a deterrent ('time cost') in deciding on the next shop to visit. Therefore, the nearest shop would be selected if all other factors were equal in a choice scenario (Haghani and Sarvi 2016).

4.1.4 Shop Preference

Each individual shop has its own attractiveness to passengers. Shop preference evaluation is activated when heuristic shoppers do not have a planned shop in sight. If the visible shops were not included in the passengers' original plan, they will choose another shop with the highest attraction level, or they might decide to move on. This attractiveness of shops was represented by shop floor space as a proxy for shop preference.

4.1.5 Crowdedness Level

As a threshold, based on the International Air Transport Association (2004)'s definition of level of service, 2.7 square meters per passenger was used. The participating airport's floorplan was used to calculate the shop capacity threshold based on each shop's available space. Once a shop reaches its capacity threshold (i.e., 2.7 square meters per passenger), passengers stop visiting because it would be deemed overcrowded.

4.2 Integrating Passenger Shopping Behavior Model and Agent-based Environment

4.2.1 Terminal layout and facilities

The base simulation model was constructed according to the configuration of the airport's departure terminal in 2019. The airport authority provided a detailed floor plan of the linear airport terminal, and it was replicated in the AnyLogic softwareto scale. The airport's airside facilities were simulated according to the provided floor plan, and areas were allocated to each facility as shown in Figure 4.

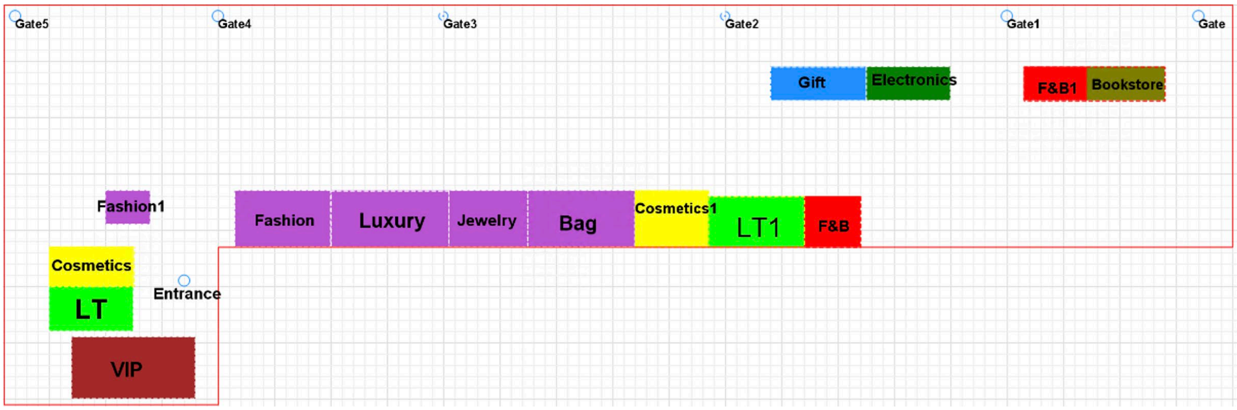

Figure 4: Terminal floor plan used in the simulation.

Altogether, there were 14 retail stores in the international terminal's airside area when the data collection exercise was conducted. Table 2 summarizes the facility profile. We categorized retail stores based on their main products offered. The conversion rate (i.e., the purchase/visit ratio) and the time and money spent per shop were calculated using the collected data. Based on observations from the two data collection exercises, passengers generally end their movement when they reach the boarding gate or spend the remainder of the dwell time in the VIP lounge.

Table 2: Facility profile.

Shop Name	Product offered	Shop Category
Bookstore	Reading materials	Art and Bookstore
Bag	Fashion & accessories	Fashion
Cosmetics	Cosmetics & perfume	Cosmetics
Cosmetics 1	Cosmetics & perfume	Cosmetics
Electronics	Electronic products	Electronics
Fashion	Sunglasses & shoes	Fashion
Fashion 1	Polo shirts	Fashion
F&B	Food & beverages (Asian style)	F&B
F&B 1	Food & beverages (Western style café)	F&B
Gift	Local products	Specialty
Jewelry	Fashion & accessories	Fashion
Luxury	Clothing & shoes	Fashion
L&T	Liquor & Tobacco	L&T
L&T 1	Liquor & Tobacco	L&T
Boarding gate	NA	NA
VIP lounge	NA	NA

4.2.2 An Example: Simulation Agent A

Table 3 shows the model inputs for the heuristic shoppers in the simulation. These parameters were obtained with the data collection at the airport. The average browsing time, conversion rate (number of purchases/visits), and average expenditure at a specific shop type were calculated. We here use a simulated agent - Agent A, as an example to explain how the heuristic model integrates with the simulation environment. In this example, Agent A is a male leisure traveler who has 2 hours of free dwell time to spend on the airside of the terminal. Agent A would move towards his boarding gate according to his direction heuristics. Given 2 hours of remaining dwell time, he has 92% probability of staying in the shopping area and 8% probability of moving towards the boarding gate directly. In this simulation instance, Agent A remains in the shopping area, and some retail shops are visible to him based on the setting of visual distance.

If we assume only L&T 1 and the cosmetics store are visible to him, Agent A would first check his plan to see if any of these two stores are his planned visit stores. If neither of these stores was included in Agent A's plan, he could choose an alternative shop to visit or continue to move towards the boarding gate. Assuming Agent A chooses to visit the L&T 1 store with the condition that the store is not overcrowded, he would spend on-average 6.9 minutes (see Table 3) in the store and has an 88% chance of spending $1,795.10 NTD ($64 USD) in this shop. The visited L&T 1 store would record a new visitor, as well as the purchase amount (if a purchase was made). This completes the first loop of Agent A's thought process as illustrated in Figure 2.

Table 3: Parameter and settings for heuristic shoppers (A superscript refers to (Schultz et al. 2010)).

Simulation Elements	**Parameters Adopted in Simulation**
Population (gender)	Probability
- Male	- 0.53
- Female	- 0.47
Travel purpose	Probability
- Business	- 0.70
- Leisure	- 0.30
Walking speed	Speed Distribution (meters/second)
- Female	- N (1.27, 0.22) [A]
- Male	- N (1.40, 0.22) [A]
Free dwell time	Normal truncated (5, 212, 56, 31.5) minutes
Boarding gate	Boarding gate allocation distribution
- Gate	- 16%
- Gate 1	- 12%
- Gate 2	- 0
- Gate 3	- 52%
- Gate 4	- 18%
- Gate 5	- 1%
Shop name	Avg. visit time (mins)/conversion/avg. expenditure (NTD)
- Bookstore	- 16.4/ 29%/ $697
- Bag	- 7.8/ 50%/ $5,370
- Cosmetics	- 6.6/ 47%/ $4,025
- Cosmetics 1	- 6.4/ 50%/ $1,696
- Luxury	- 7.0/ 50%/ $10,200
- F&B	- 22.9/ 92%/ $245
- F&B 1	- 14.8/ 78%/ $135
- Gift	- 6.9/ 63%/ $910
- Fashion	- 5.6/ 0%/ $0
- Fashion 1	- 9.0/0%/$0
- L&T	- 6.5/84%/$2,550
- L&T 1	- 6.9/88%/$1,795
- Electronic	- 13.6/40%/$9,659
- Jewellery	- 3.5/0%/$0

After visiting the L&T 1 shop, Agent A's free remaining dwell time is reduced, depending on how long the agent stays in the L&T shop. He would have an increased probability of moving to the boarding gate.

As he starts to move towards the direction of the boarding gate, Agent A would start his second loop of thought process. He could choose to visit a second shop if he is still located within the shopping area. His remaining dwell time would be further reduced by visiting the second shop. As his dwell time decreases, his probability of visiting other shops decreases and the likelihood of moving to his boarding gate would increase based on the time heuristics. He would eventually reach his boarding gate and cease all activities; at such time, the Agent A simulation would end.

5 MODEL VERIFICATION, CALIBRATION AND VALIDATION

5.1 Verification

Because the AnyLogic simulation software could present the simulation model in 2D or 3D, animation verification was conducted to observe whether the simulation's graphic display was realistic. Given the simulation's model design, the agent should behave like an airport passenger while sharing similar traits to pedestrians. See Table 4 for an observation from the beginning to the end of a simulation. The simulated agent's behavior aligned with the expected behavior, thus completing animation verification.

Table 4: Animation verification.

Expected Behaviour	Simulation Behaviour
• All agents appeared at the entrance	• All agents appeared at the entrance
• Agent's movement speed is reasonable	• Realistic (no 'flying' of the agent was observed)
• Agent's occupation of space is reasonable	• Realistic (no agent was observed to move on top of another)
• All agents moved to the boarding gate by the end of the simulation.	• Realistic (no agent being 'trapped' was observed).

5.2 Calibration

The model was calibrated by comparing the observed shop visits from the data collection exercises with the simulated visits. The absolute percentage error (APE) values across all 14 facilities were totaled and recorded. The values of the shop utility were adjusted systematically with AnyLogic's calibration function to minimize the APE. One thousand runs were conducted, and the calibration process was considered complete when the absolute percentage errors converged to less than 1% (see Figure 5).

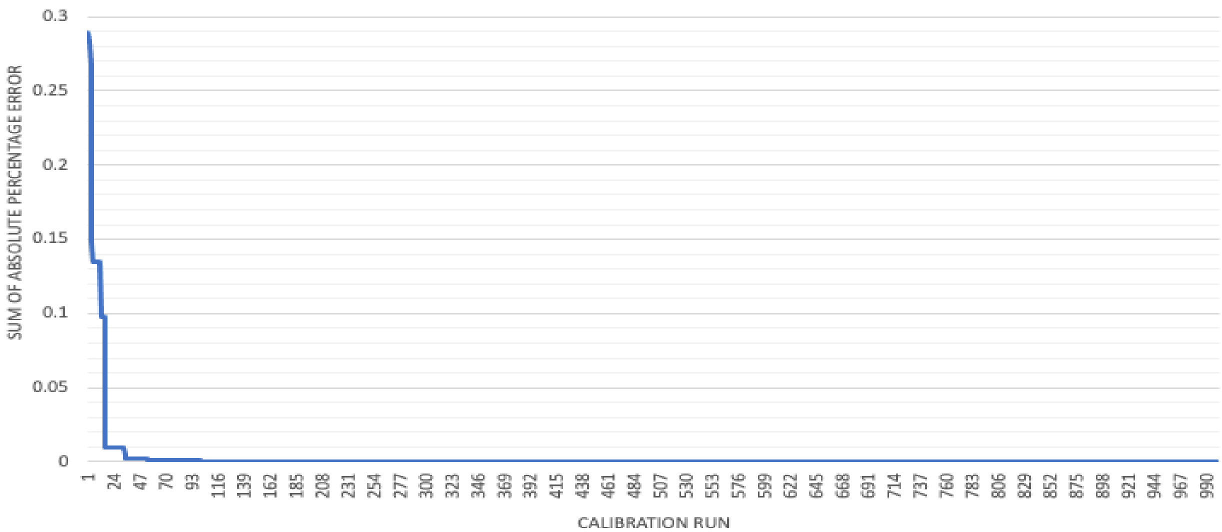

Figure 5: Calibration for heuristic shoppers.

5.3 Validation

To test the performance of the proposed model, a data set collected in 2018 was used as secondary data in this study. The data collection in 2018 was conducted at the same airport using the same procedures as the quantitative study in 2019. 397 valid samples were collected and used to test the performance of the model in relation to footfall at each shop. Because the 2018 sample size was not large (397), the footfall of each passenger type per shop could be low. To draw meaningful comparisons in the simulation validations, passenger retail shopping behavior was assumed to be unchanged regardless of passenger numbers at the airport. For example, if the sample size were increased by a factor of 100, then the visiting numbers for the simulated population would proportionally increase by the same factor. Therefore, the simulation population was increased by a factor of 100 to 39,700. The simulated result was compared with the actual visit count based on the 2018 questionnaire data (after the visit count was increased by a factor of 100). The calibrated parameters were used in the validation.

The actual total footfall was 7,400 (after an increase by a factor of 100) and the predicted total footfall from the simulation was 8,527; 1.2% APE. For the footfall in each shop, the biggest APE occurred for the jewelry store (13.5%). In the questionnaire data, the jewelry store had the lowest actual visit count—two recorded visits only. Although the number of simulation agents was increased by a factor of 100, the expected simulation visit count was only 200. Therefore, the APE value for shops such as the jewelry shop is more sensitive because of a smaller denominator value when calculating APE; this situation was also observed for the fashion shops and cosmetics shops. The MAPE across all shops in general for this simulation was 5.3%.

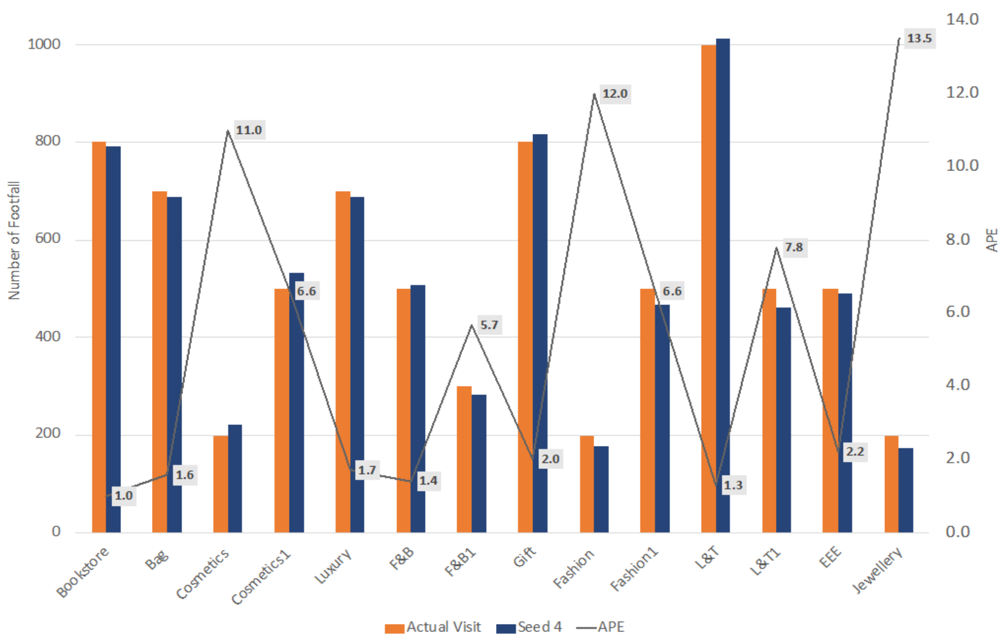

Figure 6: Data validation with simulations.

5.4 Benchmarking Validation Result

The literature has not published many agent-based simulation models for airport retail, so it is challenging to compare our model performance. To facilitate comparison, the current model validation was compared with models from existing general retail literature as shown in Table 5. Borgers et al. (2009) and Zhu and Timmermans (2011) did not provide direct APE or MAPE of their models but did provide both the actual and simulated numbers, which we used to calculate the APE. The simulation results in this research show that the heuristic model (MAPE: 5.3) performed reasonably well against other models in the literature.

Table 5: Validation result comparison.

Authors	Applied Area	Model Validation Result
Kurose et al. (2001)	Shopping center	Stop Sequence: 85% accuracy in prediction Route choice: 78% accuracy in prediction
Borgers et al. (2009)	Shopping street	Choice-sequence heuristic model: 4.2 (APE in total footfall)
Zhu and Timmermans (2011)	Shopping street	Heuristic model: 3.1 (APE on total footfall) MNL: 5.2 (APE on total footfall)
Chen et al. (2019)	Airport retail	Gravity model: 2.0 (MAPE across all shops)
Model presented in this paper	Airport retail	Heuristic model: 1.2 (APE on total footfall) Heuristic model: 5.3 (MAPE across all shops)

6 CONCLUSION AND FUTURE RESEARCH

This paper presented the development of a heuristic-bsed shopping behavior model with agent-based simulation. The validation result demonstrates that the proposed model can suitably simulate a specific group of airport passengers' shopping behavior, which established a reliable foundation for future simulation scenario studies. There are some limitations to the modeling approach. First, although using mobile eye-tracking is a novel method, it presented technical and practical challenges. For example, although participants were told to act as they would usually do (i.e., without an eye tracker), it would be naive to assume that the eye tracker did not influence their behavior at all. Second, calibration helped to ensure that the MAPE across all shops' footfall is relatively small. However, certain shops (such as fashion and jewelry) did have high APE due to the small visit counts observed in data collection. Future studies could build on this research with multiple data sources and a bigger sample size. Future data could also include more factors (e.g., time of day) in modeling passenger behavior to improve the realism of the model.

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