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Technology planning in the hotel industry☆

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ABSTRACT

The hospitality industry has turned to technology as a strategic weapon to improve operational efficiency, boost competitive edge, improve service quality, support employees, and maintain guest relationships. Hence, this paper is about technology planning in the hotel industry. We propose a prescriptive methodology to strategically select technologies which best serve the hotel. Based on LDA, HITS, and PageRank algorithms, we construct a network connecting "hotel selection criteria," "activities," and "technologies." The results present the technologies' rankings based on the HITS or PageRank weights, utilizing a network analysis. Considering the technologies' costs and the hotel's budget, we formulate an optimization model using the Knapsack problem. We demonstrate how our methodology can be applied to plan technology investments in a hotel with a numerical example.

1. Introduction

Technology's rapid development is driving the hospitality industry to inevitably adapt to various technologies (Dalgic & Birdir, 2020). Technology plays a crucial role in improving operation efficiency, supporting employees, enhancing service quality, gaining competitive advantages, and keeping a good relationship with guests within hotel companies (Cobanoglu, Ryan, & Beck, 1999; Kasavana & Cahill, 2007; Beldona & Cobanoglu, 2007; Almomani, Nasseef, Bataine, & Ayoub, 2017; Beldona, Schwartz, & Zhang, 2018). It provides hotel owners with a wide range of revenue-generating and cost-saving opportunities and helps them reach new levels of profitability. Hotels can adopt new technological developments to create tangible and intangible products through various technologies (Han, Kim, & Srivastava, 1998). A meaningful research question to be addressed is how to plan technology for the hotel so that the hospitality industry's technical evolution can be guided towards its future goals. There are two main research streams (Lee, Barker, & Kandampully, 2003; Brewer, Kim, Schrier, & Farrish, 2008): (1) satisfying guests' wants; (2) improving employee productivity. Research in the first stream focuses on utilizing technology to enhance guest service so that hospitality products will become more valuable and guests will become loyal (Verma, Victorino, Karniouchina, & Feickert, 2007). Technology is significant to any hotel organization as it can also improve its long-term financial outcome (Gummesson, 1999). The second research stream aims to improve employee productivity and increase profits. With technology, information can be distributed across departments in a hotel and among different levels of staff, thus enabling hotel employees to perform more efficiently and effectively.

It has been thirty years since the first research stream was introduced by Dan and Sandler (1992). Their article discussed the use of various technologies to improve the service in the hotel industry. They used a questionnaire to identify the most beneficial, the least beneficial, and the most significant future technologies. Lee et al. (2003) examined the questionnaire to determine how international hotel managers view technology adoption. Their results indicated the percentage of hotels that provided a specific technology. They also indicated that most managers strongly agreed on the significance of technology in enhancing guest loyalty. Sharma (2016) interviewed managers and hotel owners to research how hotels adopted various technologies to enhance the guest experience. They found that guests value technology-based amenities as a valuable addition, thus improving guests' satisfaction. Brochado, Rita, and Margarido (2016) developed a questionnaire for upscale hotel guests. They researched which current and latest technologies are important to enhance the guests' experience. They also interviewed hotel managers to ensure that managers' and guests' perceptions were aligned. Chan, Okumus, and Chan (2017) investigated the use of environmental technologies in hotels by interviewing hotel professionals. This study revealed the environmental technologies most

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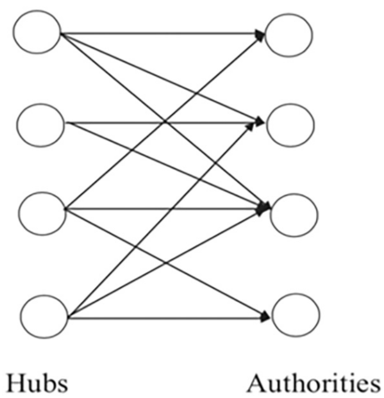

Fig. 1. Hubs and Authorities in HITS.

commonly used and the specific technologies hotel professionals preferred. Kozmal, Ahmed Mohamed Saleh, El-latief, and Fathey (2021) surveyed guests to determine how individual-level importance affected hospitality technology planning, displaying the most critical technologies from the guest perceptions.

Under the second research stream, Ham, Kim, and Jeong (2005) used the questionnaire data to examine the effect of IT applications in hotel operations. Their study found that front-office applications, restaurant and banquet management systems, and customer-facing applications significantly affected lodging operations and made them more profitable. Karadag and Dumanoglu (2009) concluded that hotel managers regard guest-related IT applications positively. In the lodging industry, guest-related IT applications and productivity are strongly related.

The literature mentioned above merely explored survey or interview data obtained from managers, hotel owners, and guests, so these studies are qualitative and subjective. The data collection procedures are both time-consuming and expensive. Furthermore, these studies are descriptive in nature and based on past data, which cannot be applied for future technology planning. Therefore, we aim to combine both research directions, considering guests' wants and hoteliers' concerns. We want to offer hotel managers and owners a tool for effective and competitive technology planning. We propose a prescriptive methodology in this paper that can be applied to select various technologies in the hospitality industry. The methodology is based on three algorithms LDA (Blei, Ng, & Jordan, 2003), HITS (Kleinberg, 1998), and PageRank (Brin & Page, 1998; Page, Brin, Motwani, & Winograd, 1999), indicating that our methodology is quantitative and objective. To the best of our knowledge, our paper is the first to propose a prescriptive methodology for selecting technologies in the hotel industry. Also, our paper is the first to use algorithms LDA, HITS, or PageRank to rank technologies in the hotel industry. Furthermore, considering the weights within the network, the existing methodologies cannot solve our problem; thus we propose a modified version of HITS and PageRank algorithms.

The first step is identifying the customer-driven hotel selection criteria and determining the weights associated with each criterion based on text mining, specifically LDA, as discussed in Section 2.1. We also identify guest-related activities by service blueprint and activity-related technologies using the literature survey and informal conversations with a few hoteliers. Then, we build a network connecting "hotel selection criteria," "activities," and "technologies." To rank technologies within the network, we develop modified versions of HITS and PageRank because existing methods cannot address the issue. We also factor in financial constraints, including the technologies' costs and the hotel's budget, and then formulate an optimization model based on the Knapsack problem.

Section two describes the theoretical background of our methodology, LDA, HITS, and PageRank. The third section introduces the methodology in detail, while the fourth section provides an illustrative case study of its use in planning hotel technologies. Section five presents a conclusion, and section six discusses theoretical and managerial implications.

2. Theoretical reference

The technical background of our methodology is presented in this section. Section 2.1 introduces LDA, the tool for obtaining the guests' hotel selection criteria, and the weights for each criterion from the reviews dataset. In Sections 2.2 and 2.3, we discuss the HITS and PageRank. These two algorithms are the basis for our methodology to prioritize technologies within the network.

2.1. Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a generative probabilistic model that can be used to describe collections of discrete data such as text corpora. LDA is a hierarchical Bayesian model consisting of three levels. A text document is modeled as a finite mixture of underlying topics, and every topic can be modeled as an infinite mixture of underlying topic probabilities. Under the topic modeling setting, text documents can be represented explicitly by topic probabilities. Based on the 'bag of words' assumption, the order of words is neglected (Blei et al., 2003).

Below are the formal definitions of the terms used by the LDA. A word is the basic unit of discrete data. The vth word in the vocabulary is represented by a V-vector w such that $w^v = 1$ and $w^u = 0$ for u $\neq$ v. A document is a sequence of N words denoted by $\mathbf{w} = (w_1, w_2, \ldots, w_N)$, where w_n is the nth word in the sequence. A corpus is a collection of M documents denoted by D = $\{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_M\}$. For each document **w** in a corpus D, the generative process of the LDA algorithm (Blei et al., 2003) is given as follows:

1 Choose the number of words N $\sim$ Poission(ϵ).
2 Choose the topic distribution $\theta \sim$ Dirichlet(α).
3 For each of the N words w_n:
  (a) Choose a topic $z_n \sim$ Multinomial(θ).
  (b) Choose a word w_n from p($w_n|z_n, \beta$), a multinomial probability conditioned on the topic z_n.

based on the topic distribution and word distribution, α and β are hyperparameters of the Dirichlet prior (Blei et al., 2003). For these hyperparameters, values larger than one result in smooth distributions over topics or words, whereas values below one result in sparse distributions over fewer topics or words (Bastani, Namavari, & Shaffer, 2019). The two main outputs of the LDA are topics and their weights (importance) in each document θ.

2.2. Hyperlink Induced Topic Search

Hyperlink Induced Topic Search (HITS) (Kleinberg, 1998) rates web pages considering the link structures among a set of web pages. A good hub is defined as a web page that points to many good authorities. A good authority is defined as a web page pointed to by many good hubs. Authorities and hubs exhibit *mutually reinforcing relationships*. An illustration of this relationship can be found in Fig. 1. Nodes represent web pages, and directed edges between two nodes indicate link relationships between two web pages.

Each web page p is then assigned a non-negative authority weight x_p and a non-negative hub weight y_p. According to Shen, Shen, and Fan (2009), hub weight indicates the quality of its links to other pages, while the authority weight indicates its content quality. The following formulas are used to calculate authority weights and hub weights (Kleinberg, 1998):

$$x_p := \sum_{q \to p} y_q \tag{1}$$

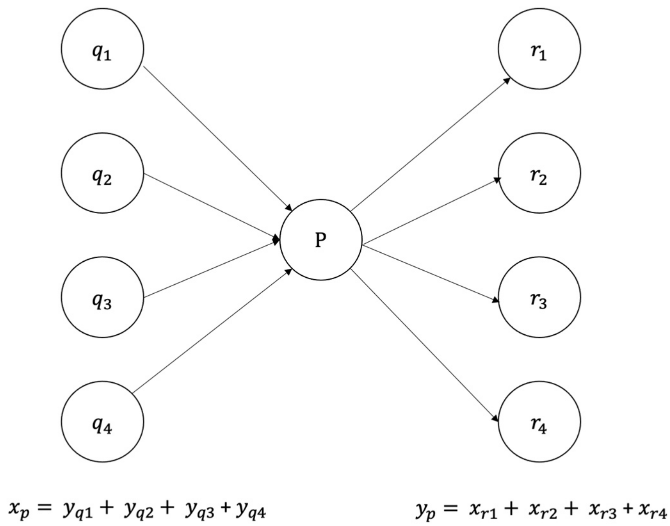

Fig. 2. An example of HITS operation.

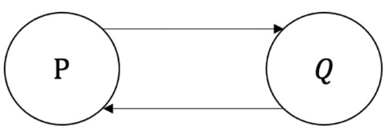

Fig. 3. An example.

$$y_p := \sum_{p \to q} x_q \tag{2}$$

Normalize x_p and y_p so that $\sum_p x_p^2 = \sum_p y_p^2 = 1$.

A convergence of the algorithm is demonstrated by Kleinberg, proving the algorithm will terminate. Generally, the algorithm converges after about ten iterations. Fig. 2 shows how hub weights and authority weights are calculated.

The HITS is modified in practical applications to suppress the contribution of different web pages from one host (Bharat & Henzinger, 1998). More applications and developments are discussed in Kleinberg (1998); Bharat and Henzinger (1998); Chakrabarti et al. (1999); Kumar, Raghavan, Rajagopalan, and Tomkins (1999); Cohn and Chang (2000); Borodin, Roberts, Rosenthal, and Tsaparas (2001); Lempel and Moran (2001); Ng, Zheng, and Jordan (2001).

2.3. PageRank

PageRank (Brin & Page, 1998; Page et al., 1999) rates web pages objectively and mechanically, effectively measuring the human interest and attention devoted to them. It ranks every web page based on the network of the web. By using the following model, it determines the significance of pages based on their link structure, constructed by hyperlinks between pages. Nodes represent web pages, and Hyperlinks among web pages are denoted as links.

$$PR(i) = \frac{1-\alpha}{n} + \alpha \sum_{j \in G(i)} \frac{PR(j)}{OutDegree(j)} \tag{3}$$

$G(i) : j \in G(i)$ if node j links to node i
Out-Degree(j): the number of links originating from node j
n: the number of nodes in a network
α: a damping factor that can be set between 0 and 1, usually set to 0.85

Fig. 3 shows the simplest example network: two pages, each pointing to the other:

$$PR(P) = \frac{1-\alpha}{n} + \alpha \frac{PR(Q)}{OutDegree(Q)} = \frac{0.15}{2} + 0.85PR(Q)$$

$$PR(Q) = \frac{1-\alpha}{n} + \alpha \frac{PR(P)}{OutDegree(P)} = \frac{0.15}{2} + 0.85PR(P)$$

The benefit of PageRank is that it considers both the degree of influence and the influence of neighboring nodes when detecting node influence. A medium-sized workstation can compute PageRank for 26 million web pages in a few hours (Brin & Page, 1998).

3. Methodology

The purpose of this paper is to plan the selection of technologies in the hotel industry. The proposed methodology is based on LDA (Blei et al., 2003), HITS (Kleinberg, 1998), and PageRank (Brin & Page, 1998; Page et al., 1999) algorithms. We use the following steps to demonstrate our methodology, see Fig. 4.

Step 1: Identify hotel selection criteria - what guests want.

The objective of step 1 is to determine the guests' hotel selection criteria. This step reflects our methodology of considering guests' needs. Therefore, it is the basis for the technology planning process. Previous scholars used the survey or interview data obtained from managers to identify the hotel selection criteria. We will use the text mining methodology Latent Dirichlet Allocation to determine what guests want from the hotel reviews dataset. So, the criteria for selecting a hotel are

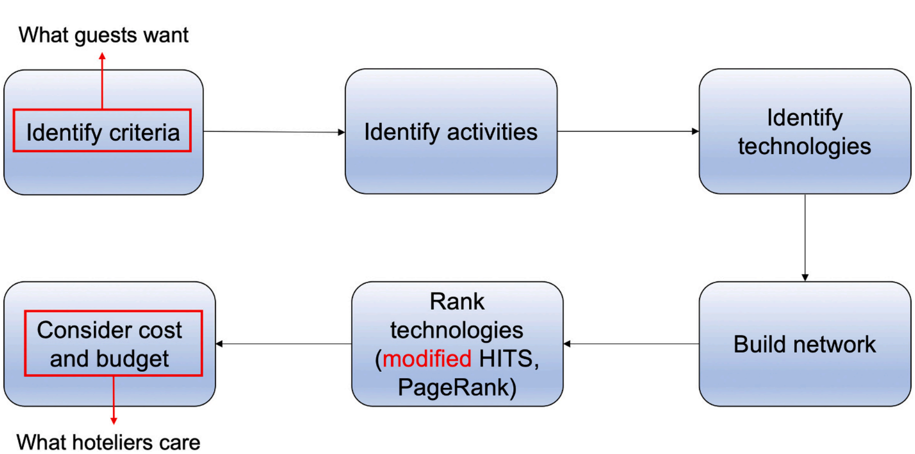

Fig. 4. The framework of our methodology.

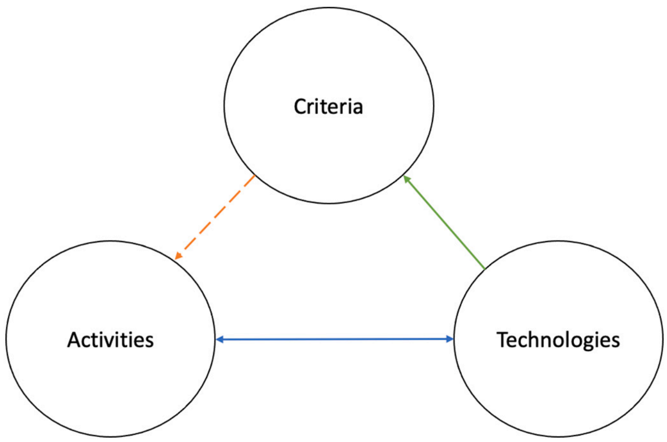

Fig. 5. Example network connecting criteria, activities, and technologies.

determined directly by guests rather than hoteliers. A detailed demonstration of the text mining procedure is displayed in Section 4.1.

Step 2: Identify activities using the service blueprint.

In step 2, we draw the hotel's service blueprint to identify activities related to guests' wants. A service blueprint (Zeithaml, Bitner, & Gremler, 2018) is a map that accurately depicts the service activities. It is a two-dimensional representation of a service process. The horizontal axis shows the chronological progression of guest and provider actions over time. The vertical axis distinguishes different areas of action. A detailed identification of the guest-related activities is displayed in Section 4.2.

Step 3: Identify technologies.

This step aims to identify the hotel technologies relevant to hotel activities in step 2, using a literature survey or informal conversations with hotel managers. Technologies can enhance guests' experiences and improve hotel operations. It is crucial to the entire technology planning process that we identify the candidate technologies here for future selection. There is a wide range of sophisticated technologies from which hotel managers can identify important ones in order to satisfy guests' needs. Detailed identification of relevant technologies is shown in Section 4.3.

Step 4: Build a network connecting criteria, activities, and technologies.

In this step, we build a network to connect 'hotel selection criteria', 'activities', and 'technologies'. This network is necessary for technology planning as we need to prioritize technology within the network. We demonstrate this network using one example shown in Fig. 5. Firstly, criteria influence the activities. For instance, 'clean, comfortable, and well-maintained rooms' is the hotel selection criterion, impacting the 'housekeeping' activity. Therefore, we construct the unidirectional orange link from criteria directing to activities that are affected. The orange link is shown as the dashed line in Fig. 5, displaying that it is weighted because each criterion is associated with a weight. Secondly, activities affect technologies. For instance, activity 'check-in' requires guests to wait in long lines. Thus the technology of 'mobile check-in' was invented. At the same time, technologies affect activities. The technology 'mobile check-in' affects the activity 'check-in' as it allows guests to check in remotely using the mobile application. Hence, the bidirectional blue link is constructed between associating activities and technologies. It is shown as the solid line in Fig. 5 because no weight is associated with it. Thirdly, technologies also determine the criteria as they are reshaping the industry. For example, the technology 'smart parking system' changes guests' viewpoints about the criterion 'car parking', so guests expect a more intelligent and convenient experience for parking. In this case, we establish the unidirectional green link from technologies directing to criteria if a path is available from the specific criterion to the specific activity, then to the specific technology. The green link is also solid since no weight is associated with it. The implementation of this step is in Section 4.4.

Step 5: Implement the proposed modified HITS and PageRank to rank technologies.

In this step, we propose modified HITS and PageRank algorithms considering the weights within the network. In addition, we apply the modified HITS and PageRank algorithms on the network to prioritize technologies. Because this paper's objective is to plan technologies in the hotel industry, we need to know each technology's importance and ranking, which can be obtained from this step. There are two reasons that we apply both algorithms. Firstly, we use the modified PageRank ranking outcomes to verify that modified HITS ranking outcomes are reasonable. Secondly, since modified HITS ranking is bi-dimensional, including hub and authority weights, while modified PageRank weight is uni-dimensional, we intend to check any statistically significant difference between the two ranking results.

We demonstrate these two ranking algorithms using one simulated example in Fig. 6. There is one criterion A; two activities 1 and 2; and three technologies a, b, and c.

Step 5.1 The modified HITS algorithm

Step 5.1.1 Propose a modified HITS algorithm

Each node i is assigned a hub weight y_i and an authority weight x_i, all initialized to 1. We also consider the weight of link p → q, denoted as w_{pq}. Here w_{pq} and w_{qp} are equal. Then x's and y's are iteratively updated as the following formula:

Repeat:

$$x_p := \sum_{q \to p} w_{qp} y_q \tag{4}$$

$$y_p := \sum_{p \to q} w_{pq} x_q \tag{5}$$

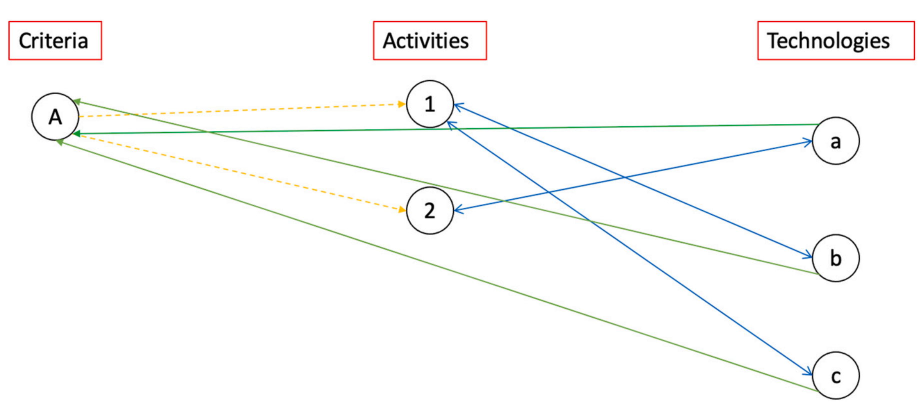

Fig. 6. An example of a network.

Normalizing x and y in each iteration.

Until Convergence.

Step 5.1.2 Implement a modified HITS algorithm

Applying the modified HITS on the network in Fig. 6, we obtain the following equations:

$$x_A = \sum_{q\to A} w_{qA} y_q = w_{aA} y_a + w_{bA} y_b + w_{cA} y_c$$

$$y_A = \sum_{A\to q} w_{Aq} x_q = w_{A1} x_1 + w_{A2} x_2$$

$$x_1 = \sum_{q\to 1} w_{q1} y_q = w_{A1} y_A + w_{b1} y_b + w_{c1} y_c$$

$$y_1 = \sum_{1\to q} w_{1q} x_q = w_{1b} x_b + w_{1c} x_c$$

$$x_2 = \sum_{q\to 2} w_{q2} y_q = w_{A2} y_A + w_{a2} y_a$$

$$y_2 = \sum_{2\to q} w_{2q} x_q = w_{2a} x_a$$

$$x_a = \sum_{q\to a} w_{qa} y_q = w_{2a} y_2$$

$$y_a = \sum_{a\to q} w_{aq} x_q = w_{a2} x_2 + w_{aA} x_A$$

$$x_b = \sum_{q\to b} w_{qb} y_q = w_{1b} y_1$$

$$y_b = \sum_{b\to q} w_{bq} x_q = w_{bA} x_A$$

$$x_c = \sum_{q\to c} w_{qc} y_q = w_{1c} y_1$$

$$y_c = \sum_{c\to q} w_{cq} x_q = w_{cA} x_A + w_{c1} x_1$$

After endless repetitions of the algorithm, the nodes' final hub and authority weights are determined. Because applying the updating rule directly and iteratively leads to diverging values, the matrix must be normalized after every iteration. This will eventually result in convergent values. We prove the convergence of x and y vectors, i.e., that the algorithm terminates in appendix I. We obtain the HITS ranking of the technologies a, b, and c by descending hub weights as technologies are all hubs with zero authority weight.

Step 5.2 The modified PageRank algorithm

Step 5.2.1 Propose a modified PageRank algorithm

We associate with each node i a PageRank weight PR_i, all initialized to $\frac{1}{n}$. n is the number of nodes in a network. We also consider the weight of link p → q, denoted as w_{pq}. Here w_{pq} and w_{qp} are equal. α is the probability of being linked to a node and is generally set around 0.85 (Brin & Page, 1998). Out-Degree(q) is the number of links originating from node q.

Repeat:

$$PR_p := \frac{1-\alpha}{n} + \alpha \sum_{q\to p} \frac{w_{pq} PR_q}{OutDegree(q)} \tag{6}$$

Until Convergence.

Step 5.2.2 Implement a modified PageRank algorithm

Applying the modified PageRank on the network in Fig. 6, we obtain the following equations:

$$PR_A = \frac{1-\alpha}{n} + \alpha \sum_{q\to A} \frac{w_{Aq} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85\left(w_{Aa} PR_a + \frac{w_{Ab} PR_b}{2} + \frac{w_{Ac} PR_c}{2}\right)$$

$$PR_1 = \frac{1-\alpha}{n} + \alpha \sum_{q\to 1} \frac{w_{1q} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85\left(w_{1a} PR_a + \frac{w_{1b} PR_b}{2} + \frac{w_{1c} PR_c}{2}\right)$$

$$PR_2 = \frac{1-\alpha}{n} + \alpha \sum_{q\to 2} \frac{w_{2q} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85\left(\frac{w_{2A} PR_A}{2} + \frac{w_{2a} PR_a}{2}\right)$$

$$PR_a = \frac{1-\alpha}{n} + \alpha \sum_{q\to a} \frac{w_{aq} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85 w_{a2} PR_2$$

$$PR_b = \frac{1-\alpha}{n} + \alpha \sum_{q\to b} \frac{w_{bq} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85 \frac{w_{b1} PR_1}{2}$$

$$PR_c = \frac{1-\alpha}{n} + \alpha \sum_{q\to c} \frac{w_{cq} PR_q}{OutDegree(q)} = \frac{1-0.85}{6} + 0.85 \frac{w_{c1} PR_1}{2}$$

After an infinite number of iterations, the PageRank weights of nodes are determined. In appendix II, we prove that the algorithm converges quickly. We obtain the PageRank ranking of the technologies a, b, and c by descending PageRank weights. The implementation of this step is presented in Section 4.5.

Step 6: Include financial constraints.

In the previous steps, we take hotel selection criteria which are guests' wants, guest-related activities, and activity-related technologies into account. To apply our methodology to the real-world case, we also need to consider the cost of technologies since most hotels have budget constraints. For each technology, we consider the initial investment cost, the fixed cost, and the variable cost. The initial investment cost is the one-time cost to obtain the technology, such as the cost of installment or making the application. The fixed cost is the cost of the technology regardless of the number of guests per time unit. For example, the cost of equipment maintenance and repair. A variable cost is the technology's cost that varies with the number of guests per time unit. For instance, the electricity and gas cost for operating the technology. We present the total cost (TC) function for technology i in the following equation:

$$TC_i = c_i + f_i t_i + e_i t_i \tag{7}$$

c_i is the initial investment cost of technology i, f_i is the fixed cost of technology i per time unit, e_i is the variable cost of technology i per time unit, and t_i is the time to launch the technology i.

Then, we formalize the model using the Knapsack problem. The model is to maximize the importance of technology investments within the hotel's budget constraint, given that each technology can be either invested or not. n is the number of technologies. We present the importance w_i of the technology i in the following equation:

$$w_i = (n+1) - rank(\text{technology i}) \tag{8}$$

Let $[x]$ denote the integer closest to x. Here

$$rank(\text{technology i}) = \left[\frac{\text{HITS ranking(technology i)} + \text{PageRank ranking(technology i)}}{2}\right] \quad (9)$$

x_i is the number of the technology i, restricted to either 0 or 1. B is the budget limit of the hotel.

$$\max \sum_{i=1}^{n} w_i x_i \quad (10)$$

Subject to:

$$\sum_{i=1}^{n} (c_i + f_i t_i + e_i t_i) x_i \leqslant B \quad (11)$$

$$x_i \in \{0, 1\} \quad (12)$$

The next section will show how to implement this methodology using a numerical example.

4. A numerical example

As an illustration of our methodology, we present a numerical example in this section.

4.1. Identify hotel selection criteria - what guests want

We implemented LDA models on the hotel reviews dataset from TripAdvisor.com. The dataset contains 101,706 records. The mean document length is 89.29 words, and the median is 82 words. We conducted the LDA analysis by Python wrapper from McCallum (2002). Based on LDA analysis, we can determine the outcomes of topics β and topic proportions θ. The topics are regarded as the guests' criteria for selecting hotels, and topic proportions are regarded as their respective weights. Table 1 summarizes twelve hotel selection criteria in column 2, which are 'clean, comfortable, and well-maintained rooms', 'safety and security', 'hotel rewards program', 'car parking', 'opportunities for relaxation', 'advertising and hotel reputation', 'room rates', 'tangibles', 'reliability', 'responsiveness', 'assurance', and 'empathy'.

Also, Hill (1995) used the term order-winning criteria to represent competitive dimensions that differentiate products. Furthermore, he said that some criteria are qualifiers because these dimensions are necessary for a product to stay on the market. The hotel type determines the order-winning criteria and qualifiers. For example, seeking a luxury hotel might be based on the order-winning criteria, reliability and responsiveness, as well as the qualifiers such as safety and security. Therefore, the weight associated with the selection criteria is important for planning technologies, which is why the orange link directing from criteria to activities in Fig. 5 is dashed. We obtained these weights from text mining. Table 1 also lists the weight for each criterion in column 3.

Table 1
The weight of hotel selection criteria.

1	2	3
No.	Hotel selection criteria	Weight
1	Clean, comfortable, and well-maintained rooms	0.1666
2	Safety and security	0.1223
3	Hotel rewards program	0.0182
4	Car parking	0.0408
5	Opportunities for relaxation	0.1832
6	Advertising and hotel reputation	0.0182
7	Room rates	0.0182
8	Tangibles	0.0608
9	Reliability	0.0765
10	Responsiveness	0.0816
11	Assurance	0.0336
12	Empathy	0.1800

4.2. Identify activities using the service blueprint

The hotel's service blueprint is created in Fig. 7, which is based on the blueprint for a hotel found in Bitner (1993) with some modifications. Fig. 7 clearly shows hotel guests' activities, both their interactions with hotel employees and the other actions that guests perform on their own as part of the hotel service, such as sleeping, eating, and drinking. The purpose of this blueprint is to identify guest-related activities from the guests' point of view (Peace & Onuoha, 2017). Guests who check in at the front desk and bellmen who deliver bags perform onstage actions. Additionally, employees might be assigned backstage duties such as arranging the food tray and preparing the food. The support processes such as updating the registration system and housekeeping are also important. Then, hotel employees' eighteen activities are identified from No. 13 to No. 30 in Table 2. Here we ignore personal activities, such as eating and drinking or receiving bags, because they do not involve technologies.

4.3. Identify technologies

In this step, we identify the hotel technologies relevant to hotel activities in Fig. 7. For example, instead of a bellman delivering bags, hotels now employ robots for luggage transportation (Reis, Melão, Salvadorinho, Soares, & Rosete, 2020). Also, regarding check-in activities, hotels are turning to new technologies such as mobile check-in (Gibbs, Gretzel, & Saltzman, 2016), robots (Reis et al., 2020), and chatbots (Ukpabi, Aslam, & Karjaluoto, 2019) to save labor costs. We identify the relevant nine hotel technologies from No. 31 to No. 39 in Table 2, which are smart energy management (Sari, 2018), mobile check-in/check-out/reservation/room keys (Gibbs et al., 2016), smart parking system (Cynthia, Priya, & Gopinath, 2018), robot (Reis et al., 2020), chatbots (Ukpabi et al., 2019), voice control (Kolavennu, Gardner, Sobanko, Knecht, & Mahasenan, 2020), facial recognition (Morosan, 2020), RFID bracelet (Tiliute & Condratov, 2014), and predictive maintenance (Longart, 2020).

4.4. Build a network connecting criteria, activities, and technologies

To visualize the technology planning in hotels, we firstly create 39 nodes corresponding to twelve 'hotel selection criteria', eighteen 'guest-related activities', and nine 'activity-related technologies' listed in Table 2. Then we determine the linking relationship among them as follows:

- **Criteria affect activities:**
  Criterion 1 → Activity 24
  Criterion 2 → Activity 21
  Criterion 3 → Activities 13, 14, 19, 20, 25, 29, 30
  Criterion 4 → Activities 15, 29, 30
  Criterion 5 → Activities 16, 23, 25
  Criterion 6 → Activities 13, 14
  Criterion 7 → Activities 13, 14
  Criterion 8 → Activities 13, 14, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30

Table 2
The rankings by HITS and PageRank.

1 No.	2 Representation	3 Authority weight	4 Hub weight	5 HITS ranking	6 PageRank weight	7 PageRank ranking
1	Clean, comfortable, and well-maintained rooms	0.0122	0.0004		0.0087	
2	Safety and security	0.0217	0.0005		0.0106	
3	Hotel rewards program	0.0574	0.0009		0.0216	
4	Car parking	0.0246	0.0005		0.0115	
5	Opportunities for relaxation	0.0525	0.0038		0.0202	
6	Advertising and hotel reputation	0.0448	0.0003		0.0168	
7	Room rates	0.0448	0.0003		0.0168	
8	Tangibles	0.0686	0.0050		0.0268	
9	Reliability	0.0686	0.0041		0.0268	
10	Responsiveness	0.0686	0.0043		0.0268	
11	Assurance	0.0512	0.0012		0.0196	
12	Empathy	0.0574	0.0056		0.0216	
13	Reservation	0.0449	0		0.0352	
14	Provide hotel information and price	0.0450	0		0.0445	
15	Arrive at hotel and parking	0.0065	0		0.0192	
16	Consult tourist information	0.0330	0		0.0304	
17	Luggage transportation	0.0122	0		0.0101	
18	Greet and take bags	0.0124	0		0.0195	
19	Check-in	0.0348	0		0.0184	
20	Process registration	0.0350	0		0.0278	
21	Go to room	0.0218	0		0.0245	
22	Deliver bags	0.0123	0		0.0136	
23	Turn on HVAC/light/voice assistant, shower, sleep	0.0264	0		0.0233	
24	Housekeeping	0.0123	0		0.0210	
25	Call room service	0.0449	0		0.0294	
26	Take food order	0.0120	0		0.0103	
27	Prepare food	0.0123	0		0.0136	
28	Deliver food	0.0123	0		0.0136	
29	Check-out and leave	0.0246	0		0.0188	
30	Process check-out	0.0247	0		0.0254	
31	Smart energy management	0	0.0518	8	0.0088	8
32	Mobile check-in/check-out/reservation/room keys	0	0.1700	2	0.0683	2
33	Smart parking system	0	0.0906	5	0.0327	5
34	Robot	0	0.1732	1	0.1315	1
35	Chatbot	0	0.1506	3	0.0487	3
36	Voice control	0	0.1419	4	0.0406	4
37	Facial recognition	0	0.0500	9	0.0108	7
38	RFID bracelet	0	0.0878	6	0.0233	6
39	Predictive maintenance	0	0.0571	7	0.0088	8

Table 3
Parameter values for the numerical example.

1 i	2 Representation	3 HITS ranking	4 PageRank ranking	5 Overall ranking	6 Importance (w_i)	7 Initial investment cost (c_i)	8 Annual fixed cost (f_i)	9 Daily variable cost (e_i)	Total cost (TC_i)
1	Smart energy management	8	8	8	2	500,000	110,000	1,000	975,000
2	Mobile check-in/check-out/ reservation/room keys	2	2	2	8	78,000	48,600	200	199,600
3	Smart parking system	5	5	5	5	203,900	461,960	500	848,360
4	Robot	1	1	1	9	150,000	10,000	2,000	890,000
5	Chatbot	3	3	3	7	150,000	60,000	1,500	757,500
6	Voice control	4	4	4	6	200,000	10,000	1,800	867,000
7	Facial recognition	9	7	8	2	18,000	6,000	700	279,500
8	RFID bracelet	6	6	6	4	100,000	1,000	200	174,000
9	Predictive maintenance	7	8	8	2	100,000	86,000	1,200	624,000

Criterion 9 → Activities 14, 15, 16, 18, 20, 21, 22, 23, 24, 26, 27, 28, 30
Criterion 10 → Activities 14, 15, 16, 18, 20, 21, 22, 23, 24, 26, 27, 28, 30
Criterion 11 → Activities 14, 15, 16, 18, 20, 25
Criterion 12 → Activities 14, 15, 16, 18, 20, 30

- **Activities affect technologies:**
  Activity 13 → Technologies 32, 34, 35, 36
  Activity 14 → Technologies 32, 34, 35, 36
  Activity 15 → Technology 33
  Activity 16 → Technologies 34, 35, 36
  Activity 17 → Technology 34
  Activity 18 → Technology 34
  Activity 19 → Technologies 32, 34, 35
  Activity 20 → Technologies 32, 34, 35
  Activity 21 → Technologies 32, 37, 38
  Activity 22 → Technology 34
  Activity 23 → Technologies 31, 34, 36, 39
  Activity 24 → Technology 34
  Activity 25 → Technologies 32, 34, 35, 36
  Activity 26 → Technology 32
  Activity 27 → Technology 34
  Activity 28 → Technology 34
  Activity 29 → Technologies 32, 33, 38
  Activity 30 → Technologies 32, 33, 38
- **Technologies affect activities:**
  Technology 32 → Activities 13, 14, 19, 20, 21, 25, 26, 29, 30
  Technology 33 → Activities 15, 29, 30
  Technology 34 → Activities 13, 14, 16, 17, 18, 19, 20, 22, 23, 24, 25, 27, 28
  Technology 35 → Activities 13, 14, 16, 19, 20, 25
  Technology 36 → Activities 13, 14, 16, 23, 25
  Technology 37 → Activity 21
  Technology 38 → Activities 21, 29, 30
  Technology 39 → Activity 23
- **Technologies affect criteria:**
  Technology 31 → Criteria 5, 8, 9, 10
  Technology 32 → Criteria 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
  Technology 33 → Criteria 3, 4, 8, 9, 10, 11, 12
  Technology 34 → Criteria 1, 3, 5, 6, 7, 8, 9, 10, 11, 12
  Technology 35 → Criteria 3, 5, 6, 7, 8, 9, 10, 11, 12
  Technology 36 → Criteria 3, 5, 6, 7, 8, 9, 10, 11, 12
  Technology 37 → Criteria 2, 8, 9, 10
  Technology 38 → Criteria 2, 3, 4, 8, 9, 10, 12
  Technology 39 → Criteria 5, 8, 9, 10

Based on the link relationship mentioned above, we construct the network shown in Fig. 8. In this figure, nodes represent hotel selection criteria, activities, and technologies. The links between nodes display the linking relationships discussed above.

4.5. Implement HITS and PageRank to rank technologies

The authority and hub weights from implementing the HITS algorithm are displayed in columns 3 and 4 of Table 2. The PageRank weights from implementing the PageRank algorithm are shown in column 6 of Table 2. Then, we first rank technologies from No. 31 to No. 39 by descending hub weights to obtain the HITS ranking in column 5. Additionally, we rank these technologies by descending PageRank weights to get the PageRank ranking in column 7.

Comparing columns 5 and 7, we find that most elements of the two ranking results are the same. So PageRank ranking results justify HITS ranking outcomes. These two rankings are then compared using the Wilcoxon signed-rank test. As a result of the p-value being 0.5, the null hypothesis that the two medians of ranking results are the same, is not rejected. Also, compared with PageRank ranking, HITS ranking can differentiate between technology 31 (smart energy management) and technology 39 (predictive maintenance). However, PageRank regards them as equal.

According to the ranking outcome, the robot is ranked first by both algorithms. Mobile check-in/check-out/reservation/room keys, chatbot, and voice control are ranked second, third, and fourth by both algorithms. Facial recognition, predictive maintenance, and smart energy management are the three least important technologies by both algorithms. The model values the number of links or interactions, indicating that the more links technology connects to activities and criteria, then more important the technology is. The three least important technologies are ranked lower because the number of links connecting to them is much less than those connecting to the most important technologies, such as the robot.

4.6. Include financial constraints

Let us assume the hotel plans to implement new technologies with the budget limit, B, of \$3,000,000. We assume that there are 1,000 rooms in the hotel to install these technologies. Technology 1 to 3, 5, 7, and 9 are systems or applications. Thus, their initial investment costs are for launching the system or making the application. Their fixed costs are for maintaining and repairing the system and applications. The parameter values are derived from the previous literature (Hildahl, 2020; Gahbauer, 2014; Salary.com, 2022; Thinkmobiles, 2021; Hughart, 2022; station, 2011; Dickinson, 2017; Threlfall, 2021; Alkhaldi, 2022; Wu, 2020), displayed in Table 3. The unit price for the technology 4, robot, is estimated to be \$150,000 (RobotWorx, 2021). The annual fixed cost of the robot is estimated to be \$10,000 (WOVO, 2021). The unit price for the technology 6, a voice-controlled assistant, is estimated to be \$200 (Segan & Greenwald, 2021). Since there are 1000 rooms in the hotel, so the initial investment cost of employing a voice-controlled assistant is estimated to be \$200,000. The annual fixed cost of the voice-controlled assistant is estimated to be \$10,000. The unit price for the technology 8, an RFID bracelet, is around \$100 (RFIDJournal, 2021). We also assume that the hotel welcomes 1000 guests per day, so employing an RFID bracelet's initial investment cost is \$100,000. The annual fixed cost of RFID bracelets is estimated to be around \$1,000 (Peter, Stephen, & Molly, 2002). The variable costs are the electricity and gas cost for operating these technologies per day. A technology's total cost includes its initial investment cost, annual fixed cost, and variable cost during the year.

The overall ranking, displayed in column 5 of Table 3, is calculated by Eq. (9). The importance of the technology i, which is w_i from Eq. (8), displayed in column 6 of Table 3. For example, the overall ranking of smart energy management is 8, and then its importance is $9 + 1 - 8 = 2$. Based on the parameter values in Table 3, the model is shown as follows:

$$\begin{aligned}\max\ & 2x_1 + 8x_2 + 5x_3 + 9x_4 + 7x_5 \\ & +6x_6 + 2x_7 + 4x_8 + 2x_9\end{aligned}$$

Subject to:

$$\begin{aligned}&975,000x_1 + 199,600x_2 + 848,360x_3 + 890,000x_4 + 757,500x_5 \\ &+867,000x_6 + 279,500x_7 + 174,000x_8 + 624,000x_9 \leqslant 3,000,000 \\ &\qquad x_i \in \{0,1\}, i \in \{1,2,3,\ldots,9\}\end{aligned}$$

By solving the above optimization problem, the hotel should invest in technology 2, 4, 5, 6, and 8 with total spending of $2,888,100.

5. Conclusion

We present a prescriptive methodology of hotel technology planning in this paper. The methodology is based on the algorithms LDA, HITS, and PageRank to prioritize technologies. In the first step, we identify hotel selection criteria using text mining methodology, specifically LDA. In the second step, the guest-related activities are identified by service blueprinting. In the third step, the new technologies relevant to the activities are determined using the literature survey and informal conversations with a few hoteliers. The fourth step builds the network connecting hotel selection criteria, activities, and technologies. The fifth step proposes the modified HITS and PageRank algorithms on the network to obtain authority, hub, and PageRank weights. Then we rank technologies by descending hub weights or PageRank weights respectively to obtain two ranking outcomes. The final step uses the Knapsack problem to maximize the total importance of selected technologies considering the costs and the hotel's budget. Finally, in Section 4, an example is demonstrated in a step-by-step procedure.

From Table 2, we find that the authority weights for activity No. 13 to activity No. 30 are non-zero, but the hub weights are zero. While the authority weights for technology No. 31 to technology No. 39 are zero, their hub weights are non-zero. The authority and hub weights for criterion No. 1 to criterion No. 12 are non-zero. According to Section 2.2, activities are authorities, and technologies are hubs. This suggests that if an activity is important, it is pointed to by many significant technologies. If a technology is important, it points to many significant activities. Under the setting of technology investment in hotels, the objective is to make sure activities work well. Hence, activities are authorities. Technologies are hubs because they are tools for both guests and employees to complete activities. The hotel selection criteria are neither authorities nor hubs, connecting activities and technologies. A specific technology with high hub weight displays that it points to important activities. Also, since the link relationship among the criteria, activities, and technologies are the same for both modified HITS and PageRank algorithms, the two ranking results are almost the same.

To include the financial considerations in our methodology, we obtained the estimated parameter values of the initial investment cost, fixed cost, and the variable cost for each technology using the literature survey. After solving the Knapsack problem, which aims to maximize the sum importance of the technologies within the hotel's budget, we conclude that the hotel should invest in mobile check-in/check-out/reservation/room keys, the robot, chatbots, voice control, and RFID bracelets.

This paper has presented a prescriptive methodology considering both guests' wants and hoteliers' concerns relating to the choice of technology in the hotel industry. This methodology raises several interesting questions that deserve further investigation. Firstly, it might be challenging to implement our methodology in a real-world scenario, so the evaluation of the method using field studies is essential. Secondly, the majority of feasible technologies are screened based on financial factors. In reality, the trade-off exists among guests' requirements and the hotel's financial considerations. Therefore, a definitive treatment of guests' wants and financial aspects within a unified framework is highly desirable. Thirdly, the methodology in our study might also consider the risk that the technology does not perform well. For example, will the robot function well in a specific hotel? If it will not, what is the extra cost of adjusting or replacing the technology? Another avenue for future research would be to discuss the privacy issues associated with the technologies such as chatbots, facial recognition, and so on. Therefore, some guests might still prefer the traditional service provided by hotel employees. Lastly, the technological evaluation presented in this research may present an opposing viewpoint. Rather than comparing given technologies concerning particular guest's wants, one might question where we need technology in various hotel activities and the characteristics that should be included in that technology.

6. Theoretical and managerial implications

6.1. Theoretical implications

This paper proposes a methodology for selecting new technologies that hotels can utilize. In order to allocate budgets for selecting technologies, the study integrates guests' wants with an optimization model. The study identifies four gaps from previous research. First, traditional methodologies prioritize technologies based on survey or interview data (Lee et al., 2003; Sharma, 2016), which is descriptive. However, our methodology is prescriptive and incorporates the effects of all components in the system.

Secondly, previous studies have been qualitative and subjective in prioritizing technologies (Dan & Sandler, 1992; Brochado et al., 2016). In contrast, our methodology is based on the LDA, HITS, and PageRank, and its calculation procedure involves actual links and weights, which are quantitative and objective.

The third gap is that previous methodologies fail to account for either guests' preferences or financial considerations (Kozmal et al., 2021). This paper considers what guests want, which represents the marketing aspect. In addition, we look at the cost of technologies that could improve operational efficiency, which is the operational aspect.

Fourthly, previous literature ignores the interaction among hotel selection criteria, hotel activities, and hotel technologies (Ham et al., 2005; Karadag & Dumanoglu, 2009). The network-based nature of our methodology allows us to consider how hotel selection criteria, activities, and technologies interact.

6.2. Managerial implications

Despite the importance of guests' wants, few studies have done integration of guests' requirements and costs associated with each technology, which is the focus of our proposed methodology. Misallocation of the budget on the wrong technologies leads to a substantial loss in practice. The proposed methodology assists the management team in considering the importance of the guests' preferences and associated costs in strategic technology planning. The proposed methodology can help implement technology planning in other service firms, such as restaurants, banks, and hospitals, and it is not explicitly limited to usage in the hotel industry. Although we believe that implementing our methodology could be challenging for novice users, with the help of facilitators familiar with text mining and network-based algorithms, this could be implemented easily.

CRediT authorship contribution statement

Jin Fang: Conceptualization, Methodology, Software, Validation, Formal-analysis, Investigation, Data-curation, Writing-original-draft, Visualization. **Fariborz Y. Partovi:** Conceptualization, Methodology, Resources, Writing-review-editing, Supervision, Project-administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I

We prove that the proposed modified HITS algorithm terminates.

Lemma 1. *The proposed modified HITS algorithm terminates, i.e., the x and y vectors eventually converge (Kleinberg, 1998).*

Proof. Let $N = (S,L)$, with $S = \{node_1, node_2, \dots, node_n\}$ and L is the set of links between nodes. Let $W = (w_{ij})$ denote the weight matrix of the network N; w_{ij} is equal to the weight of link $i\rightarrow j$ if there is a link between $node_i$ and $node_j$ and is equal to 0 otherwise. Then step (4) and (5) can be rewritten as:

$$x := W^{\top} y \tag{13}$$

$$y := Wx \tag{14}$$

Let z denote the vector $(1,1,1,\dots,1) \in \mathbb{R}^n$. Then after k iterations, the authority weight vector x^k is the unit vector in the direction of $(W^{\top}W)^{k-1}W^{\top}z$ and hub weight vector y^k is the unit vector in the direction of $(WW^{\top})^k z$.

Van Loan and Golub (1983) stated the standard result of linear algebra that if M is a symmetric $n \times n$ matrix, and v is a vector not orthogonal to the principal eigenvector $\omega_1(M)$ then the unit vector in the direction of $M^k v$ converges to $\omega_1(M)$ as k increases without bound. Additionally, if M has only non-negative entries, then the principal eigenvector of M has only non-negative entries.

Since $W^{\top}W$ is symmetric and nonnegative matrix, z isn't orthogonal to the principal eigenvector $\omega_1(W^{\top}W)$, then sequence $\{y^k\}$ converges to a limit y^*. In addition, $W^{\top}z$ isn't orthogonal to the principal eigenvector $\omega_1(W^{\top}W)$ and sequence $\{x^k\}$ converges to a limit x^*.

Appendix II

We prove that the proposed modified PageRank algorithm terminates.

Lemma 2. *The proposed modified PageRank algorithm terminates, i.e.,PR_peventually converges.*

Proof. The PageRank weight of node p after t iterations is $PR_p^{(t)}$. We initially set $PR_p^{(0)} = \frac{1}{n}$. To calculate the new PageRank weight, we will use the following equation.

$$PR_p^{(t)} = \frac{1-\alpha}{n} + \alpha \sum_{q\rightarrow p} \frac{w_{pq} PR_q^{(t-1)}}{OutDegree(q)}$$

The solution will eventually converge to the true PageRank solution after a few iterations. To prove that the convergence time is small, we define PR_p^* as the true PageRank weight of node p. Then we can define the total error at step t to be

$$Error(t) = \sum_p |PR_p^{(t)} - PR_p^*|$$

PR_p^* being the true solution, it must satisfy the PageRank equations exactly:

$$PR_p^{(*)} = \frac{1-\alpha}{n} + \alpha \sum_{q\rightarrow p} \frac{w_{pq} PR_q^*}{OutDegree(q)}$$

To find the error, we subtract this from the iterative method equations, and obtain:

$$PR_p^{(t)} - PR_p^{(*)} = \alpha \sum_{q\rightarrow p} \frac{w_{pq}(PR_q^{(t-1)} - PR_q^*)}{OutDegree(q)}$$

We use the Triangle Inequality to get the expression for the error in PageRank weight of the node p at step t:

$$Error(t) = \sum_p |PR_p^{(t)} - PR_p^*| \leqslant \sum_p |\alpha \sum_{q\rightarrow p} \frac{w_{pq}(PR_q^{(t-1)} - PR_q^*)}{OutDegree(q)}|$$

Since $w_{pq} \leqslant 1$, we have the following

$$Error(t) \leqslant \sum_p |\alpha \sum_{q\rightarrow p} \frac{(PR_q^{(t-1)} - PR_q^*)}{OutDegree(q)}|$$

The node q will occur OutDegree(q) times on the right-hand side, and since there is an OutDegree(q) on the denominator, these will cancel.

$$Error(t) = \sum_p |PR_p^{(t)} - PR_p^*| \leqslant \alpha \sum_q |PR_q^{(t-1)} - PR_q^*| = \alpha Error(t-1)$$

As $\alpha \leqslant 1$, the decrease in total error is compounding, indicating fast convergence.

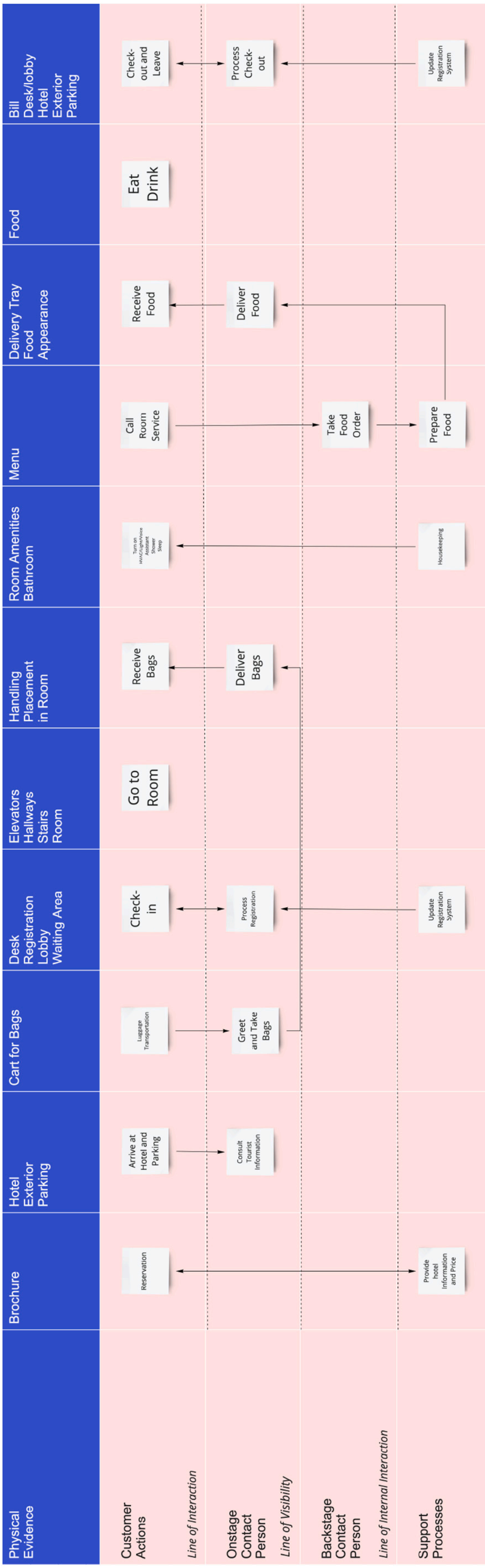

Fig. 7. Blueprint for hotel.

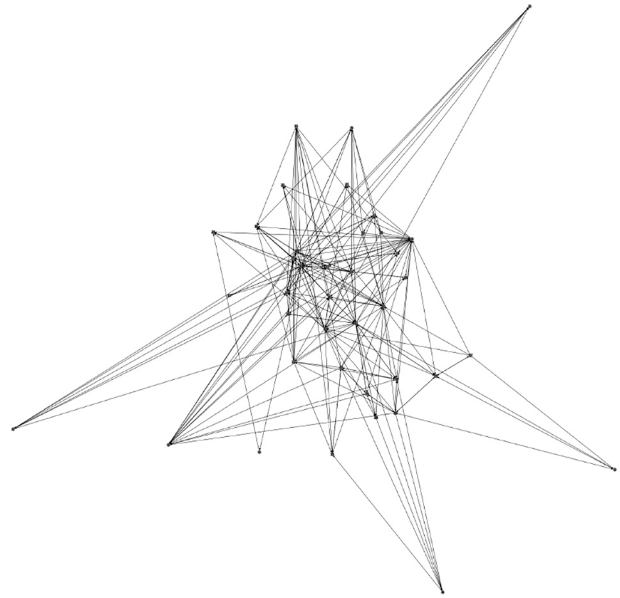

Fig. 8. Network connecting hotel selection criteria, activities, and technologies.

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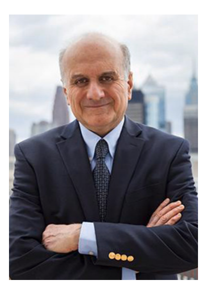

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