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ORIGINAL RESEARCH

Application of industrial engineering concepts and techniques to ambient intelligence: a case study

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Abstract Ambient intelligence (AmI) researchers have primarily come from information engineering, electrical engineering, and medical backgrounds. However, industrial engineering (IE) concepts and techniques are crucial to the sustainable development of the AmI industry. For this reason, two IE concepts and techniques, the planning cycle and cost–benefit analysis, were applied to an AmI system in this study. First, a five-step planning cycle was proposed, according to which a detailed cost–benefit analysis was performed that aggregated objectives on the client side, the server side, and in the AmI system as a whole. A restaurant recommendation system was used to illustrate the proposed methodology. The experimental results showed that the system administrator was able to perform a credible cost–benefit analysis and improve the system performance by using the proposed methodology.

Keywords Ambient intelligence (AmI) · Industrial engineering (IE) · Planning cycle · Cost–benefit analysis

1 Introduction

According to the European Commission, ambient intelligence (AmI) is a future vision in which an environment supports the people inhabiting it in an unobtrusive, interconnected, adaptable, dynamic, embedded, and intelligent way (Ducatel et al. 2001). In this vision, an environment is sensitive to the needs of its inhabitants and capable of anticipating their needs and behavior (Sadri 2011).

Existing AmI systems have several problems. First, most AmI systems have not been implemented on a commercial basis (Raper et al. 2007), and many AmI systems have also never undergone cost–benefit analyses (Cesta et al. 2002). One reason for this is because of large-scale government support whose focus is not on profit, but another reason is the difficulty of collecting cost and benefit information on the client and user sides. For example, a user may use a restaurant recommendation system but not go to the recommended restaurant, resulting in costs on the system side representing a failure of the system, despite the user having made a decision on the basis of the provided information. A benefit such as this can be difficult to measure because the system received no commission from the recommended restaurant. In addition, it is also difficult to relate the final decision of a user to the recommendation that was given. For an AmI system to be sustainable, a credible cost–benefit analysis must be conducted, which entails overcoming these problems (Tsai and Chen 2014).

Second, although an AmI application can be modeled as a human–system interaction process in which human factors and ergonomics are an indispensable part and should be emphasized, most AmI-related research has been conducted by experts with backgrounds in information engineering, electrical engineering, information management, and medicine, rather than in ergonomics. This fact is highlighted by Fig. 1, which shows the most common fields of AmI-related projects sponsored by the Taiwanese Ministry of Science and Technology from 2009 to 2013.

The operators of an AmI system can overcome these problems and pursue sustainable development by using the following methods: continuously updating databases,

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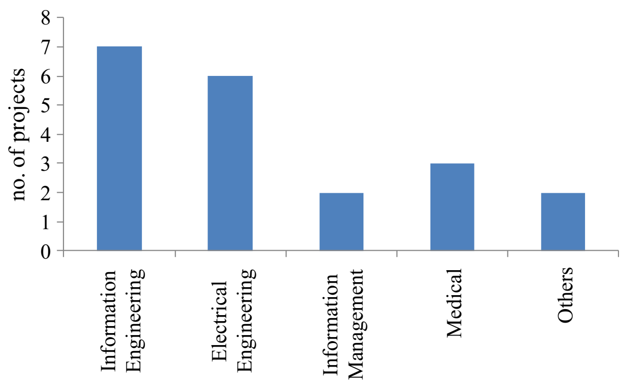


Fig. 1 Most common fields of AmI-related projects sponsored by the Taiwanese Ministry of Science and Technology from 2009 to 2013

adding new features and retiring old or unpopular services, providing more options and flexibility to users, investigating new methods of increasing profit, and improving the suitability for use (Tsai and Chen 2014). Table 1 shows methods adopted by Google Maps to improve its services (Google.com 2014).

As indicated in the foregoing discussion, continuous improvement is necessary to maintain the evolution of an AmI system, and this conforms to the basic philosophy of industrial engineering (IE), which is to continuously improve a manufacturing system or service (Shingo 1989).

Some concepts and techniques of IE may be applicable to problems encountered when developing AmI technologies. For example, the motion and time study as used in the field of operations research can decompose a task into several steps (operation, movement, checking, delaying, and storage) (Mundel and Danner 1985), to determine which steps can be supported by AmI technologies. In addition, most AmI systems detect and determine a user's posture and actions, and many IE researchers are engaged in image analysis and pattern recognition. Furthermore, ergonomics and occupational psychology concepts can be used to determine whether an AmI technology is obtrusive and to assist in the development of AmI applications on the basis of the assessment of human physiological conditions (Frederick 1984).

For these reasons, two IE concepts and techniques, the planning cycle (Shewhart 1980) and cost-benefit analysis (Griffin 1998), were applied to an AmI system in this study. First, a five-step planning cycle was proposed, according to which a detailed cost–benefit analysis that aggregates objectives on the client and user sides, the server/system side, and the AmI system as a whole. We used a restaurant recommendation system to illustrate the proposed methodology.

2 AmI industry

2.1 Taiwan as an example

Taiwan has numerous high-tech industries supporting the development of AmI. Constantly evolving microprocessors and nanotechnology have promoted the development of AmI technologies (Sadri 2011), and Taiwan's semiconductor industry plays an active role in this evolution. The Taiwanese company Foxconn is one of the original engineering manufacturers (OEMs) for the iPhone and other smartphones, which are commonly used as a client-side interface in AmI applications (STPI 2007), and the camera of the iPhone is made by Largan Precision which is also a Taiwanese company. Foxconn is also the OEM of Google Glass, a new wearable technology that supports various AmI applications, such as mobile guides, personal and mobile marketing, and virtual museums. Additionally, Taiwanese researchers are also active in the global AmI research community, particularly in location-aware services (LASs) (Table 2).

Because Taiwan is a small market, the development of the AmI industry in Taiwan is influenced by the global

Table 1 Methods adopted by Google Maps to improve its services

Year	Method	Category
2007	Launched Street View	Adding new features
2008	Allowed users to improve public map data	Improving the suitability for use
2009	Began using a proprietary geospatial database	Continuously updating databases
2010	Expanded browser support	Providing more options and flexibility
2011	Began charging for the use of its API	Investigating new methods of increasing profit
2011	Allowed users to edit Google Maps	Improving the suitability for use
2012	Allowed users to post photos and reviews of locations directly	Improving the suitability for use
2013	Launched Google Maps Engine Lite	Providing more options and flexibility
2013	Created customized maps specific to the behavior of each user	Improving the suitability for use

Table 2 Top 10 regions for research in fields related to AmI

Keyword	Top 10 regions
Ambient intelligence	Spain, Italy, United States, England, France, Netherlands, Greece, Taiwan, Germany, Portugal
Location-aware services	United States, South Korea, China, Spain, Taiwan, Italy, Japan, India, Germany, Switzerland
Mobile marketing	United States, China, South Korea, England, Germany, Spain, India, Australia, Taiwan, Italy
Smart home	United States, South Korea, China, England, Canada, Taiwan, Italy, Spain, Germany, France

According to statistics by Web of Science from 2011 to 2015

AmI industry and market. For example, radio frequency identification (RFID) is an intelligent device widely used for making general payments, as well as in locations such as smart factories (for automatic monitoring of production processes and logistics), and smart hospitals (Al Nahas and Deogun 2007). According to idtechex.com (2009), the global market for RFID amounted to \$5.56 billion in 2009, including transactions relating to tags, receivers, software, and services. The expansion of this market is clearly due to government projects such as those relating to public transportation, identification (identification cards and passports), the military, and animal tags. In Taiwan, RFID technologies have been widely implemented. For example, the largest logistics company in Taiwan, HCT Logistics, uses RFID cards to automatically monitor the arrival and exit of vehicles at collection stations. The EasyCard used in the greater Taipei region is also an application of RFID technologies (specifically Philip's MIFARE technology) to monitor the entrance and exit of subway passengers. Taiwan's RFID output value reached NT\$2.7 billion in 2009, of which high-frequency (13.56 MHz) passive tags and readers accounted for 31 %. This growth in Taiwan's RFID industry surpassed that of other countries in the same period.

Another noticeable trend is the expansion of the global market for smart homes, which was predicted by MarketsandMarkets (2011) to increase from \$5.325 billion in 2010 to approximately \$11 billion in 2015. North America is the largest market for smart homes, followed by Europe. The trend is even more prominent in the Asia–Pacific region; in Taiwan, smart houses have been designed with remote monitoring, e-learning, finger-vein identification, remote health care, and access control using smart phones.

As mentioned previously, many AmI applications developed for public use are supported by local governments in Taiwan. For example, the Taipei City Government launched a remote health care service in 2010 which automatically transmits collected blood pressure data back to its municipal database every day by using a blood pressure monitor connected to a relay gateway (Taipei City Government 2010). A medical team examines the data and provides users with recommendations to prevent the onset of chronic diseases. The data is also used to monitor physiological conditions over the long term.

2.2 AmI and IE

AmI researchers in Taiwan are mainly from information, electrical engineering, and medical backgrounds, while researchers from fields such as IE and information management remain lacking. Cook et al. (2006) established an AmI system architecture comprising four layers. Figure 2 shows how these disciplines map to the four layers.

As shown in this figure, in Taiwan, the development of the AmI industry lacks inputs from IE and information management professionals. A systemic outlook, consideration of human factors, techniques of motion analysis, and industrial engineers' ability to manufacture products economically are crucial to the sustainable development of the AmI industry (Ambient Intelligence Association of Taiwan 2013). Hence, in November 2012, the Ambient Intelligence Association of Taiwan (AIAT) was established to gather numerous scholars from IE and information engineering backgrounds (Chen et al. 2015). Other associations have also been established to support the development of various fields of AmI; Table 3 lists the most prominent such associations in Taiwan.

Exploring the possible applications of IE to AmI is necessary; hence, this study applied two IE concepts and techniques, the planning cycle and cost–benefit analysis, to an AmI system.

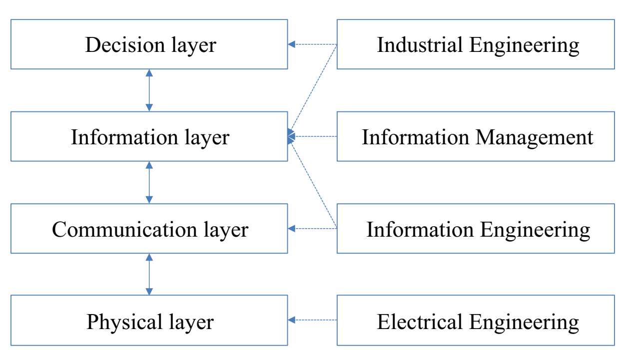


Fig. 2 Mapping disciplines to the four layers of an AmI system

Table 3 Taiwanese associations supporting the development of AmI

Name	Year founded	URL	Fields supported
Ambient Intelligence Association of Taiwan	2012	http://www.amie-tw.org	All
Chinese Society of Gerontechnology and Service Management	2009	http://gerontechnology.org.tw/	Remote health care
			Smart homes
			Telemedicine
Greater China Internet of Things	2010	http://www.gcthings.org/GCT/jsp/index.jsp	Smart homes
			Smart factories
Taiwan Intelligent Building Association	2010	http://www.tiba.org.tw/	Smart homes
			Smart factories

3 Proposed methodology

3.1 Planning cycle

To assess the performance of an AmI system, the performance of the client and user sides, that of the server and system side, and that of the system as a whole must be considered, and therefore these need to be aggregated. Hence, the planning cycle shown in Fig. 3 can be applied. This planning cycle is a modification of a common management cycle (Shewhart 1980), and consists of the following five steps.

3.2 Invest on the server side

Investment on the server and system side includes investment in hardware I_H, software I_{So}, communication bandwidth I_B, and the required expenses for maintenance and management I_M:

$$I_{total} = I_H + I_{So} + I_B + I_M \tag{1}$$

Additionally, $t = 1 \sim T$ (the planning horizon). Upgrading each part requires additional investment that can only be made in a stepwise manner. For example, as shown in Fig. 4, I_B can be increased in the following manner:

$$I_B = \begin{cases} 800 & if \quad B \leq 400 \\ 1500 & if \quad 400 < B \leq 600 \\ 3000 & if \quad 600 < B \leq 800 \end{cases} \tag{2}$$

where B is the bandwidth used.

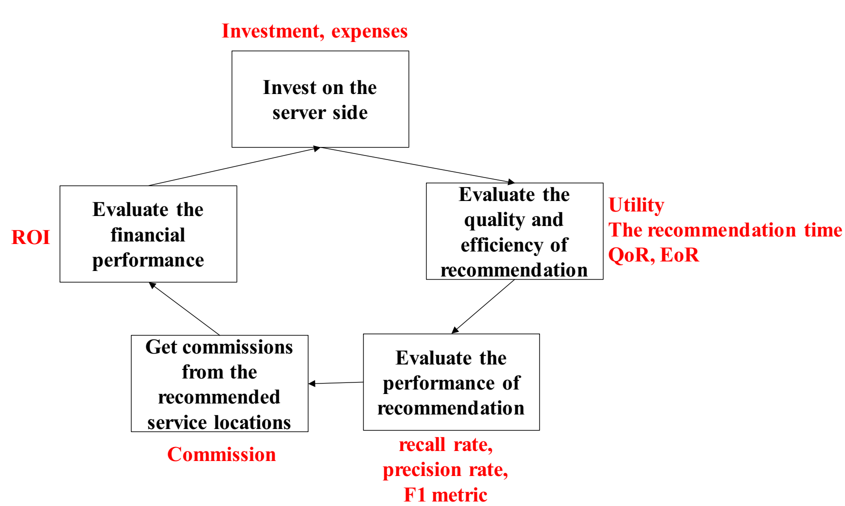
A more advanced system server is able to cover a larger area, consider more constraints, use a more sophisticated reasoning method, respond to a request within a shorter time, and handle more requests in parallel. All of these advantages are conducive to the quality and efficiency of recommendation.

3.3 Evaluate the quality and efficiency of a recommendation

The quality of recommendation QoR can be evaluated in terms of the average utility achieved for users as follows:

$$QoR = \bar{u} = \frac{\sum_{i=1}^{n} u_i}{n} \tag{3}$$

Fig. 3 Planning cycle



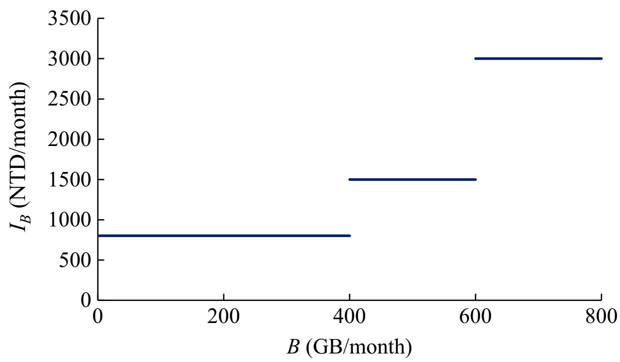


Fig. 4 Stepwise increase in I_B (using data from http://www.hinet.net)

where u_i is the utility achieved for user i and $i = 1 \sim n$. The term QoR is dependent on the capability of the system server (which is a function of I_{total}), the region area RA, constraints $[c_j]$, and the reasoning method RM, such that

$$QoR = f_1(I_{total},\ RA,\ [c_j],\ RM) \tag{4}$$

A more capable system server ($I_{total} \uparrow$) can cover a larger area ($RA \uparrow$) from which more service locations can be selected. This also results in more constraints in path planning ($|[c_j]| \uparrow$). Reasoning methods such as mathematical programming (Chen and Wu 2013; Tsai and Chen 2014; Chen 2015) can find the globally optimal solution resulting in the highest quality recommendation. This is followed by soft computing methods that can help solve AmI optimization problems that are highly complex (Astrain et al. 2006; Mateo et al. 2006; Kuo and Chen 2006; Andrienko et al. 2010; Chen 2015); however, soft computing methods are generally unable to guarantee a globally optimal solution (Wu and Chen 2015). The most prevalent methods in this field are decision rules (Astrain et al. 2006; Mateo et al. 2006; Savage et al. 2012) and heuristics (Rinner and Raubal 2004; Kuo and Chen 2006; Tsai and Chen 2014; Chen 2015). Both are easy to implement but result in low-quality recommendations. A comparison of these methods is presented in Table 4.

The efficiency of recommendation EoR is a function of the average time it takes to make a recommendation, and is obtained as follows:

$$EoR = \xi - \overline{rt} = \xi - \frac{\sum_{i=1}^{n} rt_i}{n} = \xi - \frac{\sum_{i=1}^{n} (tc_i - ts_i)}{n} \tag{5}$$

where ts_i and tc_i indicate the times at which the recommendation process for user i is started and completed, respectively, and ξ is a constant. The variable EoR is also a function of the four factors, as follows:

$$EoR = f_2(I_{total},\ AS,\ [c_j],\ RM) \tag{6}$$

3.4 Evaluate the performance of recommendations

If a user is persuaded to act in accordance with the recommendation result, he or she is highly likely to go to the recommended service location, which results in a successful recommendation.

A traditional method of evaluating the performance of a recommendation is to compare the recommendation set R_i with the action set A_i, then measure the following:

$$re_i \text{ (the recall rate) } = |A_i \cap R_i|/|A_i| \tag{7}$$

$$rp_i \text{ (the precision rate) } = |A_i \cap R_i|/|R_i| \tag{8}$$

$$\text{F1 metric } = 2 \cdot re_i \cdot rp_i/(re_i + rp_i) \tag{9}$$

In a recommendation set, the recommended service locations are associated with different utilities, and are typically sorted according to their utilities. Assume that K service locations are recommended for user i, indicated by $k = 1 \sim K$, with nonzero utilities, indicated with $u_{i(k)}$. The recommendation set can be modelled with a fuzzy set instead, as follows:

$$\tilde{R}_i = \{(k, \mu_{\tilde{R}_i}(k)) | u_{i(k)} > 0\} \tag{10}$$

where the membership of service location k is obtained as

$$\mu_{\tilde{R}_i}(k) = \frac{u_{i(k)}}{\max\limits_{l} u_{i(l)}} \tag{11}$$

Hence,

$$0 \le \mu_{\tilde{R}_i}(k) \le 1 \tag{12}$$

However, in a mobile setting, a user may be unfamiliar with the service locations. In this case, the action set does not exist. We can only compare the recommendation set with the service location that a user finally chooses. Assume that $A_i = \{S_i\}$, meaning that user i selects service location S_i. Consequently, $|A_i| = 1$, and $A_i \cap \tilde{R}_i = \{(S_i, \mu_{\tilde{R}_i}(S_i))\}$. Therefore,

$$\begin{aligned} re_i &= |A_i \cap \tilde{R}_i|/|A_i| \\ &= |\{(S_i, \mu_{\tilde{R}_i}(S_i))\}|/1 \\ &= \mu_{\tilde{R}_i}(S_i) \end{aligned} \tag{13}$$

In addition,

$$\begin{aligned} rp_i &= |A_i \cap \tilde{R}_i|/|\tilde{R}_i| \\ &= \mu_{\tilde{R}_i}(S_i) / \sum_{\mu_{\tilde{R}_i}(l) > 0} \mu_{\tilde{R}_i}(l) \end{aligned} \tag{14}$$

Theorem 1 $rp_i \le re_i$

Proof According to Eq. (11), when $u_{i(m)} = \max\limits_{l} u_{i(l)}$, $\mu_{\tilde{R}_i}(m) = 1$. Consequently,

Table 4 Comparison of reasoning methods

Reference	Method	Category	Optimality
Rinner and Raubal (2004)	Ordered weighted average	Heuristic	Nonoptimal
Astrain et al. (2006), Mateo et al. (2006)	Fuzzy inference rules	Decision rules Soft computing	Nonoptimal
Kuo and Chen (2006)	Fuzzy analytic hierarchy process	Heuristic Soft computing	Nonoptimal
Andrienko et al. (2010)	Self-organization map	Soft computing	Locally optimal
Savage et al. (2012)	Decision tree	Decision rules	Nonoptimal
Chen and Wu (2013)	Integer-nonlinear programming Forced relearning	Mathematical programming	Globally optimal
Tsai and Chen (2014)	Integer-nonlinear programming Ordered weighted average	Mathematical programming Heuristic	Near-optimal
Chen (2015)	Fuzzy integer-nonlinear programming Fuzzy Dijkstra's algorithm	Mathematical programming Heuristic Soft computing	Near-optimal

$$\sum_{\mu_{\tilde{R}_i}(l)>0} \mu_{\tilde{R}_i}(l) = \mu_{\tilde{R}_i}(m) + \sum_{\substack{\mu_{\tilde{R}_i}(l)>0 \\ l \neq m}} \mu_{\tilde{R}_i}(l) \geq 1 \tag{15}$$

according to Eq. (12). Thus,

$$rp_i = \mu_{\tilde{R}_i}(S_i) / \sum_{\mu_{\tilde{R}_i}(l)>0} \mu_{\tilde{R}_i}(l) \leq \mu_{\tilde{R}_i}(S_i) = re_i \tag{16}$$

Theorem 1 is proven.

For n users, the average performance is evaluated as follows:

$$\overline{re} = \frac{\sum_{i=1}^{n} re_i}{n} \tag{17}$$

$$\overline{rp} = \frac{\sum_{i=1}^{n} rp_i}{n} \tag{18}$$

It is reasonable to trace the relationship between these measures and the quality and efficiency of recommendation, as follows:

$$\overline{re} = f_3(QoR, EoR) \tag{19}$$

$$\overline{rp} = f_4(QoR, EoR) \tag{20}$$

3.5 Receive commission from the recommended service locations

Some AmI systems allow a user to reserve a service and pay online through a client application. In other cases a user must pay at the recommended service location. In either method, the AmI system receives a commission from the service location when a user makes a purchase. However, a user may not make a purchase after arriving at the recommended service location, in which case the AmI system does not receive a commission despite the recommendation being successful. Nevertheless, the number of successful recommendations can be expected to increase sales at service locations, and in turn greater commission. The total commission that an AmI system can receive is

$$tcm = \sum_{k=1}^{K} cm_k \tag{21}$$

where cm_k is the commission received for recommending users to service location k. Because a high number of successful recommendations increases the possibility that an AmI receives commission, it is natural to fit the following relationship:

$$tcm = f_5(\overline{re}, \overline{rp}) \tag{22}$$

After substituting Eqs. (4), (6), (19), and (20) into (22),

$$\begin{aligned} tcm &= f_5(\overline{re}, \overline{rp}) \\ &= f_5(f_3(QoR, EoR), f_4(QoR, EoR)) \\ &= f_5(f_3(f_3(f_1(I_{total}, AS, [c_j], RM), f_3(f_1(I_{total}, AS, [c_j], RM)), \\ &\quad f_4(f_3(f_1(I_{total}, AS, [c_j], RM), f_3(f_1(I_{total}, AS, [c_j], RM)))) \end{aligned} \tag{23}$$

3.6 Evaluate financial performance

The financial performance of the LAS system, measured in terms of return on investment (ROI), can be evaluated as follows:

Table 5 Investment in the LAS system and subsequent expenses

Scenario	I_H (NT\$)	I_{So} (NT\$)	I_B (NT\$/month)	I_M (NT\$/month)	I_{total} (NT\$)	RA (km^2)
1	95,000	35,000	800	33,000	941,200	4
2	85,000	20,000	3000	33,000	969,000	3
3	90,000	15,000	1500	33,000	933,000	5
4	87,500	12,500	800	33,000	911,200	5

$$\mathrm{ROI} = \frac{tcm - I_{total}}{I_{total}} \cdot 100\,\% \tag{24}$$

Another financial performance measure is the payback period (PP) that can be evaluated as follows:

$$\sum_{t=1}^{\tau} tcm(t) - \sum_{t=1}^{T} I_{total}(t) \geq 0 \tag{25}$$

where $tcm(t)$ and $I_{total}(t)$ indicate the total commission and investment during period t, respectively. T is the planning horizon. PP is the minimum of τ.

4 Illustrative example

A restaurant recommendation system (Chen 2015) was used to demonstrate the proposed methodology. The restaurant recommendation system aimed to minimize the waiting time of a user when he or she arrived at the recommended restaurant, in accordance with the just-in-time methodology. The planning horizon (T) was determined as 2 years.

Four scenarios used in the example are summarized in Table 5. The same reasoning method, the fuzzy Dijkstra's algorithm (Chen 2015), was used in all scenarios.

If user i is recommended to visit service location k, utility is evaluated as follows:

$$\begin{aligned}\tilde{u}_i &= \max\{0, 15(-)\widetilde{wt_{i(k)}}\} = \max\{0, 15(-)(rt_{i(k)}(-)\widetilde{at_{i(k)}})\} \\ &\cong \max\{0, 15 - rt_{i(k)} + \frac{at_{i(k)1} + at_{i(k)2} + at_{i(k)3}}{3}\}\end{aligned} \tag{26}$$

where $\widetilde{wt_{i(k)}}$, $rt_{i(k)}$, and $\widetilde{at_{i(k)}}$ are the waiting time, service ready time, and arrival time of user i at service location k, respectively, and $(-)$ represents fuzzy subtraction. Furthermore, $\widetilde{at_{i(k)}}$ is a fuzzy number used to account for the uncertainty of the position of user i. Consequently, $\widetilde{wt_{i(k)}}$ and $\tilde{u}_i$ are also fuzzy numbers. Hence, a service location at which a user must wait more than 15 min is assigned a zero utility and is not recommended. After defuzzification,

$$u_i = \max\{0, 15 - rt_{i(k)} + \frac{at_{i(k)1} + at_{i(k)2} + at_{i(k)3}}{3}\} \tag{27}$$

where $\widetilde{at_{i(k)}} = (at_{i(k)1}, at_{i(k)2}, at_{i(k)3})$

Table 6 shows statistics relating to utility and the recommendation time when using the restaurant recommendation system in each scenario. The quality and efficiency of recommendation, QoR and EoR, were assessed on the basis of these statistics, and ξ was set to 1. Scenarios 4 and 2 achieved higher quality and efficiency than the other scenarios. In addition, multiple linear regression (MLR) was applied to fit the relationship between QoR (or EoR) and the inputs. The fitted equations are

$$\begin{aligned}QoR &= \bar{u} = f_1(I_{total},\ RA,\ -,-) \\ &= 21.937 - 0.000018 I_{total} + 0.089 RA\end{aligned} \tag{28}$$

$$\begin{aligned}EoR &= \xi - \overline{rt} = f_2(I_{total},\ RA,\ -,-) \\ &= -0.220 + 0.0000011 I_{total} - 0.037 RA\end{aligned} \tag{29}$$

The coefficients of determination, R^2, of the two equations are 0.89 and 0.99, showing that both provide considerably close fits for the collected data.

This study also recorded whether users went to the recommended service locations. Table 7 shows the results for Scenario 1, in which $X(u)$ means the utility by recommending a user to service location X is u. The recommendation performance was then evaluated. Table 8 shows the recommendation performances of the four scenarios. Scenario 2 achieved the highest recall rate and the highest precision rate, which was due to both the quality and efficiency of recommendations. To analyze this, the relationships were also fitted using MLR equations, and the results were as follows:

$$\overline{re} = f_3(QoR,\ EoR) = 1.623 - 0.146 QoR - 0.541 EoR \tag{30}$$

$$\overline{rp} = f_4(QoR,\ EoR) = -0.094 + 0.010 QoR + 0.571 EoR \tag{31}$$

The coefficients of determination of both equations were greater than 0.90.

Table 6 Statistics relating to utility and the recommendation time

Scenario	$\bar{u}$	$\overline{rt}$ (s)
1	5.50	0.28
2	4.35	0.23
3	5.35	0.34
4	5.60	0.37

Table 7 Recommendation results (Scenario 1)

i	R_i	$\tilde{R}_i$	A_i	re_i	rp_i
1	Z (9.24), D (5.47), G (2.31)	Z (1) D (0.59), G (0.25),	unknown	0	0
2	Z (4.57), C (0.24)	Z (1)C (0.24),	Z	1	0.81
3	G (7.79), C (4.57)	G (1), C (0.59)	C	0.59	0.37
		…			
20	G (9.13), C (6.59), Z (0.12)	G (1), C (0.72), Z (0.01)	G	1	0.58

Table 8 Recommendation performances of the four scenarios

Scenario	$\overline{re}$	$\overline{rp}$
1	0.43	0.37
2	0.57	0.39
3	0.49	0.32
4	0.46	0.33

Table 9 Commission received in the four scenarios

Scenario	cm_k (NT\$)					tcm (NTD)
	1	2	3	…	K	
1	34,700	120,550	76,500	…	86,550	1,547,500
2	46,500	213,650	58,050		76,150	1,738,550
3	24,600	166,950	43,650		123,350	1,284,600
4	42,100	254,300	123,450		54,100	1,655,850

Table 10 Summary of ROI and PP evaluation results

Scenario	ROI (%)	PP (months)
1	64	15
2	79	14
3	38	17
4	82	13

Table 9 shows the total commission received from all service locations in the various scenarios. The AmI system received the greatest total commission in Scenario 2. The relationship between the total commission and the recommendation performance was fitted using an MLR equation as follows:

$$tcm = f_5(\overline{re}, \overline{rp}) = 93477 + 169638\overline{re} + 3916168\overline{rp} \quad (32)$$

which supported the proposition that successful recommendations increase the total commission.

Finally, the ROI and PP of each scenario were evaluated, and the results thereof are summarized in Table 10. Scenario 4 was the most favorable. The fitted Eqs. (28) to (32) enabled the system administrator to effectively improve the system performance. In the case of Scenario 4, to improve ROI by 5 %, for example, tcm must be increased by the same percentage to 82,793. A viable method for achieving this, according to Eq. (32), is to increase $\overline{re}$ by 0.1 and $\overline{rp}$ by 0.017. To increase $\overline{rp}$ by 0.017, EoR must be improved by 0.030, according to Eq. (31).

4.1 Conclusions and directions for future research

IE concepts and techniques are of considerable value to AmI applications. However, most research and development in the AmI industry has lacked inputs from IE, meaning that AmI applications cannot be implemented in an economical manner. It is also unclear whether the benefits of an AmI system exceed the costs. Without considering these, the AmI industry may be in another bubble. For these reasons, this study discussed the application of two IE concepts and techniques, the planning cycle and cost-benefit analysis, to an AmI system. First, a five-step planning cycle was proposed, according to which a detailed cost-benefit analysis was performed, which aggregated objectives on the client side, the server side, and the AmI system as a whole.

We used a restaurant recommendation system to demonstrate the proposed methodology. The experimental results showed the following:

1. The performances of the client side, the server side, and the system as a whole influenced each other. This complex relationship can be clarified using the proposed methodology. It is also possible to quantify this relationship using existing statistical and fuzzy computing techniques. Based on this quantified relationship, an AmI system can even optimize the objectives.
2. The system administrator was able to perform a credible cost-benefit analysis and improve the system performance by using the proposed methodology.

To further investigate the effectiveness of the proposed methodology, it should be tested in other AmI systems. In addition, other IE concepts and techniques can be applied to improve the performance of an AmI system.

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