Article

IS-DT: A New Feature Selection Method for Determining the Important Features in Programmatic Buying

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Abstract: Traditional data-driven feature selection techniques for extracting important attributes are often based on the assumption of maximizing the overall classification accuracy. However, the selected attributes are not always meaningful for practical problems. So, we need additional confirmation from the experts in the domain knowledge to determine whether these extracted features are meaningful knowledge. Moreover, due to advances in mobile devices and wireless environments, programmatic buying (PB) has become one of the critical consumer behaviors in e-commerce. However, it is extremely difficult for PB service providers to build customers’ loyalty, since PB customers require a high level of service quality and can quickly shift the purchases from one website to another. Previous studies developed various dimensions/models to measure the service quality of PB; nevertheless, they did not identify the key factors for increasing customers’ loyalty and satisfaction. Consequently, this study used an importance–satisfaction (IS) model as domain knowledge and proposed a new IS-DT feature selection method. This new IS-DT method combined the IS model and the decision tree (DT) algorithm to extract useful service quality factors for enhancing customer satisfaction and loyalty in PB. An actual case was also provided to illustrate the effectiveness of our proposed method. The results showed that for increasing customer satisfaction, the highest impact factors included “problem solving”, “punctuality”, “valence”, and “ease of use”; for building customer loyalty, the most important factors were “expertise”, “problem solving”, “information”, “single column”, “voice guidance”, “QR code”, “situation”, “tangibles”, “assurance”, “entertainment”, and “safety”. Our IS-DT method can effectively determine important service quality factors in programmatic buying.

Keywords: feature selection; programmatic buying; mobile shopping; decision tree; importance-satisfaction model

1. Introduction

Due to advances in information and communication technologies (ICTs), popularization of mobile devices, and the well-constructed environment of wireless networks, consumer behaviors have shifted from physical stores to online consumption on a large scale. Thus, manufacturers and enterprises have also shifted from traditional-market sales to Internet shops for higher potential profit margin [1]. Therefore, “programmatic buying” (PB), which generally refers to the use of computer programs to allow the right people to see the right advertising information at the right time to complete the purchase, has attracted more attention from manufacturers in various industries [2]. Yahoo’s report predicts that the global advertising market will show a V-shaped recovery in 2021, and the PB market will reach USD 155 billion [3]. At the same time, there is double-digit growth in the PB market in Taiwan, the US, Europe and China. Compared to other countries in the world, Taiwanese markets were less affected by the epidemic; the market size of programmatic buying grew by more than 30% in 2021. Seventy percent of advertisers in Taiwanese companies have recently used PB, and nearly half of them have been satisfied...
with the positive results. Therefore, programmatic buying will be a major driver of digital advertising growth [3].

In the process of PB, programmatic advertising is very important [4]. It is an emerging and rapidly developing IT phenomenon that uses huge amounts of data (big data) to disseminate deeply personalized marketing themes to target audiences [4]. Programmatic advertising [4,5] is more popular than traditional advertising due to its high degree of automation, flexibility, and cost advantages [6]. Despite its popularity and widespread use, there is a limited amount of research in this area.

Following the trend in PB, electronic commerce (e-commerce) has used the Internet to buy, sell, or support products and services. It is used for economic exchanges, information exchanges, and post-sale supports [7]. It has changed the way of conducting business and offered more competitive prices due to wider kinds of services/products and more marketing strategies. Thus, the e-commerce topic has attracted many researchers. For example, Kassim and Abdullah [8] indicated that customers’ satisfaction and trust could create customer loyalty in e-commerce. Later, the authors in [7] identified that e-trust was the highest impact factor for e-commerce and it also encouraged the use of digital resources.

Similarly, mobile commerce (m-commerce) has increasingly been one of the critical consumer behaviors in the global markets since people can use mobile services to complete business transactions without time and place boundaries. Thus, m-commerce has attracted a variety of researchers in the last two decades [9,10]. In m-commerce, there are many successful applications, such as mobile banking [11–13], ticket purchases [14], mobile payment [15], mobile learning [16], mobile games [17], and mobile shopping (M-shopping) [18–21]. Among these applications, mobile shopping (M-shopping) has been considered one of the critical markets that have very high potentials of growth [9] (Sarkar et al., 2020). Therefore, Funk [22] studied M-shopping in Japan between 2001 and 2003 and indicated that push-based emails and access to URLs in these emails were the initial drivers of the Japanese M-shopping market. He also suggested that the integration of mobile sites with other media was the major driver of M-shopping. In addition, the authors in [18] investigated the criteria for selecting M-shopping sites and included that M-shopping sites should provide (1) the right products and promotion activity, (2) functions that help consumers search, view, compare, and purchase merchandises easily and securely, and (3) refunds with flawed-product return guarantees and have a commitment to privacy protection.

Additionally, due to the increasing shopping behaviors, M-shopping customers have expected a high level of service quality. The authors in [23] believed that mobile service providers not only provide services, but also focus on improving the service quality. Therefore, researchers attempted to measure and to improve M-shopping service quality. They modified conventional SERVQUAL to make the PB model suitable for measuring the M-shopping service quality [12,23–25]. Several models have been developed to completely measure all dimensions of M-shopping service quality. Moreover, due to no space and time boundaries, and the easy availability of information, online customers can quickly shift the purchases from one website to various ones. Consequently, it is extremely difficult for M-shopping service providers to build customers’ loyalty [24] for long-term benefits and for encouraging future purchases [26]. In addition, many researchers have considered that service quality was a significant factor for customer satisfaction and loyalty [27–29]. Gefen [30] indicated that the perceived service quality has positive direct effects on customer loyalty. Kassim and Abdullah [8] also discovered that customer satisfaction appears to have a positive direct effect on trust, while both customer satisfaction and trust have direct positive effects on loyalty. Therefore, the present study aims to determine the crucial service quality factors for improving customer satisfaction and building customer loyalty.

Big data analytics (BDA) have been widely applied to understand customer behaviors [31]. It is increasingly becoming a trending practice that provides a new opportunity that is helpful in relevant decision making [32]. For example, Liu et al. [33] found small and medium-sized enterprises (SMEs) can analyze customer online reviews and the capacity on
customer insight acquisition and strategic decision making. Saggi and Jain [32] presented a methodical analysis for the usage of BDA in various applications, including agriculture, healthcare, cyber security, and smart city. Feature selection is one of the BDA techniques.

There is a wide variety of feature selection methods used to identify relevant attributes [34]. In general, the feature selection technique, which is considered a data pre-processing step, has been widely used to reduce the dimensionality of data, to decrease computational cost, and to remove irrelevant attributes and noise for improving classification performance [34,35]. Traditional data-driven feature selection techniques extract crucial attributes based on the assumption of maximizing the overall classification accuracy. However, the selected attributes, which are relevant to data classification performance, are not always meaningful for practical problems. Therefore, it is vital to select meaningful features which are hard to obtain from experts. Consequently, the present study proposed a new feature selection method, namely the IS-DT method, by integrating the importance–satisfaction (IS) model and decision tree (DT) algorithm to identify important factors associated with customer satisfaction and loyalty in programmatic buying.

2. Background and Related Works

2.1. Programmatic Buying (PB)

Due to advances in wireless network environments, consumers can see the right advertisement information at the right time and complete the purchase through computer programs. Therefore, programmatic buying (PB) has become an important factor driving the growth of digital advertising [3]. PB refers to the automated buying and selling of advertising media using technology [36]. PB is built on two well-developed tools: a data management platform (DMP) and demand side platform (DSP) [2,37–39] to resolve “the core challenge of finding the best match between a given user in a given context and a suitable advertisement” [40].

Programmatic buying involves automating the systems using technology and data supported by artificial intelligence (AI) based on tracking marketing activities on the Internet in order to improve efficiency and effectiveness of advertising activities in real time [37,39] and to enable programmatic purchasing via trading platforms [41]. In PB, machine learning (ML) algorithms can predict the performance of advertisements and select the most suitable advertisement which fits the view command of the target audience. After serving the advertisement, ML algorithms will also use real-time data to build models and better the advertisement for the following advertising rounds [38] based on the lifestyles, interests, behaviors, and demographic of customers, such as gender, generation, and economic status [2,36]. In other words, based on specific triggers, such as search words/phrases or search queries, PB automates the display and the relevant trigger according to what users individually search on their mobile phones, computers, or other technical devices. The PB process begins when a user connects to a specific webpage [37]. Compared to the traditional model of media buying, PB has more positive features, as follows:

1. **Granularity**: offers opportunities for specific recipients to purchase each individual advertising impression separately (not blocks or package ads) with their general parameters in a specific advertising environment.
2. **Real-time trading**: able to decide a specific advertiser or selected advertising impressions in real time based on the latest data.
3. **Real-time information**: displays available real-time information about potential advertising.
4. **Real-time creation**: manipulates the creative and advertising messages on an ongoing basis in an advertising environment in real time immediately after winning the bid.
5. **Automation**: offers automated processes for booking, posting, and purchasing [4,39].

PB is a new sale and purchase model [42], in which the traditional models have been replaced by fully automated individualized models [39]. Although PB is developing rapidly, it has received limited academic attention [43]. For instance, Li and Guan [44] introduced PB bidding strategies by using ML algorithms to predict win rate and winning price in
real-time bidding in mobile advertising. The authors in [37] conducted qualitative research using a panel of experts with a relevant background in the use of PB technology on a daily basis. Chen et al. [38] provided a framework for understanding programmatic creative from the advertising industry in China and discussed how big data and AI underpin PB. Kozielski and Sarna [39] assessed the impact of technology in building a competitive advantage of an organization with the example of PB. Lee [2] studied consent of the general data protection regulation in advertising technology focusing on PB.

However, from the available literature, no research focused on identifying important factors associated with customer satisfaction and loyalty in PB. Thus, programmatic buying was the research subject of this study. We proposed the IS-DT model to identify the key factors that improve the performance of PB.

2.2. Crucial Factors for Programmatic Buying (PB)

From the available literature, relatively few papers discuss service quality or determinant factors for improving the performance of PB. In this study, “mobile shopping” (M-shopping) and “mobile commerce” (m-commerce)-related factors will be our candidate features.

Trust and attitudes might be critical factors in M-shopping and m-commerce. The authors in [45] found that facilitating conditions and perceived trust was the decisive factors in e-commerce. Kao and Huillier [46] conducted an empirical analysis using a survey of attitudes and beliefs about m-commerce and social distancing. They concluded that attitudes towards social distancing were important moderators of purchasing via mobile devices. The authors in [9] studied m-commerce trust through a meta-analysis. They indicated that antecedents of m-commerce trust were perceived usefulness, perceived ease of use, system quality, information quality, service quality, user interface, perceived risk, perceived security, structural assurance, prevalence and trust tendencies; and consequences of m-commerce trust included attitudes, user satisfaction, behavioral intentions, and loyalty. In addition, all relationships, except perceived ease of use, trust tendencies, and attitudes, were culturally mediated. Nilashi et al. [47] focused on security, design, and content factors that influence customer trust in m-commerce websites.

Moreover, some studies attempted to determine m-commerce adoption factors. Verkijika Verkijika [48] studied important factors influencing consumer adoption of m-commerce applications and indicated that social influence, convenience, hedonic motivation, perceived risk, and perceived trust were significant predictors of behavioral intentions. The authors in [10] concluded that the use of m-commerce at the early preparation stage was more likely hedonic motivation (utility motivation) and tended to be used as intentionally/consciously (habitually/unconsciously) motivation. Chau and Hepu Deng [49] investigated the key determinants of m-commerce adoption by small and medium-sized enterprises (SMEs) in Vietnam.

Other studies focused on the e-service quality of m-commerce and identified important factors associated with customer loyalty. For instance, the authors in [50] aimed to build theoretical frameworks of e-service quality. Ladhari [51] first reviewed the literature regarding e-service quality and then reported various scales for measuring e-service quality, summarized methodological issues related to the development of e-service quality scales, and discussed the dimensionality of the e-service quality. They found that the most commonly used factors were reliability/fulfillment, responsiveness, web design, ease of use/usability, privacy/security, and information quality/benefit. Ding et al. [29] presented e-SELFQUAL to examine the quality of online self-services in e-retailing. Their e-SELFQUAL can be used to examine the relationships between online service quality and customer satisfaction, as well as loyalty in e-retailing. Authors in [52] studied the relationship between e-service quality dimensions (efficiency, system availability, fulfillment, and privacy) and relationship quality dimensions (satisfaction, trust, and commitment) and customer loyalty in m-commerce services. The authors in [53] studied the important factors of online shopping and found that sales and the number of high-quality negative
reviews were the most important factors affecting consumer decision making; the number of reviews and the number of reviews with pictures were relatively minor factors. Chi [54] applied an extended technology acceptance model (TAM) and used brand equity and website quality as determinants of perceived usefulness and perceived ease of use to predict Chinese consumers’ use of apparel m-commerce intent.

2.3. Feature Selection

Feature selection can be utilized to identify a feature subset that can result in the highest classification performance [55]. A number of soft computing approaches, such as neural networks [56–58], rough sets [59], least absolute shrinkage and selection operator (LASSO) [1,57,59,60], and support vector machine–recursive feature elimination (SVM-RFE) [59,60], have been successfully used to remove irrelevant, unnecessary, and redundant attributes. The conventional feature selection methods can be divided into three groups [61]. The first group includes filter-based methods which use statistical analysis techniques to extract important features without learning methods [62]. The second group involves wrapper-based methods which select factors based on the classification performance of learning methods [63]. For instance, Chang et al. [55] utilized DT, LASSO, and SVM-RFE to discover the important factors of a non-revisit factor set. [1] Chang et al., 2020b employed LASSO and SVM-RFE to select important factors that affect O2O trust. Huynh-Cam et al. [57] employed DT to identify important factors affecting the performance of first-year undergraduate students. Chen et al. [56] applied DT and LASSO to indicate successful factors of movie projects. The third group contained hybrid methods which combined filter- and wrapper-based methods [64,65]. However, when applying these feature selections to the real world, we need to consider computational cost and complexity.

One of the popular learning algorithms, which have been widely used in feature selections, are decision trees [66]. When a decision tree (DT) algorithm is used for feature selection, a tree is constructed from the collected datasets. All attributes appearing in the tree, which form the reduced subset of attributes, are assumed to be the most important, and vice versa, those disappearing in the tree are irrelevant [67]. Recently, DT-based feature selection methods, which have transformed from filter-based methods to wrapper-based decision trees (WDT), have a wide variety of successful applications [68]. For instance, Chen et al. [34] presented a support vector machine (SVM)-based model which integrates a DT dimension reduction scheme to analyze the failures of turbines in thermal-power facilities. The authors in [69] used DT to diagnose multi-component faults of a rotational mechanical system and found its significant factors based on a decision tree. Debska and Guzowska-'Swider [70] used a DT for selecting important features of food quality. Cho and Kurup [71] utilized a DT to reduce dimensionality for increasing the classification performance of electronic nose. The authors in [65] developed a DT-based light weight intrusion detection using a wrapper approach. Therefore, for the purpose of ease of use, decision tree (DT)-based feature selection methods have been employed to implement the feature selection task in this study.

Although the effectiveness of feature selection methods has been proved in many published works, some existing problems needed to be tackled. Traditional feature selection techniques select relevant attributes based on the assumption of maximizing the overall classification accuracy. However, the extracted attributes are crucial for classifying data, but not always meaningful for practical problems. Consequently, we need experts to provide additional domain knowledge to assist us in selecting crucial and meaningful factors [72].

Therefore, the present study proposed a feature selection method, namely the IS-DT method, by integrating the importance–satisfaction (I-S) model as domain knowledge and decision tree (DT) algorithms to identify important factors for customer satisfaction and loyalty in programmatic buying.
2.4. Importance–Satisfaction (IS) Model

The importance–satisfaction (IS) model (Figure 1), which is a business-friendly model, can provide entrepreneurs a brief analysis. The IS model is one of the importance–performance analysis (IPA) models. It can often be used without adequate consideration of its validity or reliability [73]. The IPA models have a wide range of successful applications in the real world. For example, IPA was used to identify performance gaps for attributes of bus services in Tehran, Iran in [73] and to analyze users’ perceptions of the importance and performance of cultural ecosystem services in urban parks in [74]. The authors in [75] used IPA to assess tourist satisfaction at a destination by identifying attributes of interest from social media texts and indirectly measuring performance and importance values. Luo et al. [76] systematically analyzed the characteristics of fake news from the perspective of readers, using IPA and canonical correlation analysis techniques. Although the IPA model is a simple structure, it can provide much useful information about a company’s quality performance. Therefore, this study used a revised model of IPA, which is called IS mode [77], and then integrated it with DT algorithms to form the IS-DT feature selection method for determining key factors in programmatic buying.

![Figure 1. Importance–Satisfaction model [77].](image)

In the IS model, the horizontal dimension and the vertical dimension show the degree of importance–satisfaction level of the quality factors, respectively. Then, the order pairs (importance scale, satisfaction scale) can be located on the coordinates. The means of the importance scale and the satisfaction scale can be used to divide the coordinate into four areas:

- **Area I: Excellent.** The quality factors positioned in this area are the major weapons for e-service providers.
- **Area II: To be improved.** The quality factors listed in this area are considered important to customers, but the performances have not met the expectations.
- **Area III: Surplus.** The quality factors located in this area are not very important to customers, but the perceptions of customers are quite satisfactory.
- **Area IV: Care-free.** It is unnecessary for entrepreneurs to care about these kinds of quality factors in this area.

3. The Proposed IS-DT Feature Selection Method

3.1. The Implemental Procedure of the IS-DT Method

The implemental procedure of our proposed IS-DT method is graphically illustrated in Figure 2. It contains eight steps: defining service quality factors of mobile shopping, designing questionnaires, modifying questionnaires, collecting data, implementing IS analysis (IS model), constructing decision trees, feature selection and identifying crucial quality factors, and drawing conclusions.
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**Figure 2.** Implemental procedure of the IS-DT proposed method.

**Step 1:** Define the service quality factors of mobile shopping.

In this step, we reviewed existing research and defined the service quality factors of programmatic buying based on the published literature.

**Step 2:** Design a questionnaire for the IS model.

In step 2, we designed a questionnaire for implementing IS analysis and building decision trees to survey the perceived satisfaction and importance.

**Step 3:** Modify the questionnaire.

The initial IS questionnaire was given to a small group of customers for piloting. Then, based on their responses, we slightly modified the IS questionnaire.

**Step 4:** Collect data.

In step 3, we collected some representative samples who have experienced programmatic buying. These samples were required to respond to our IS questionnaire.

**Step 5:** Implement IS analysis (IS model).

There are four sub-steps for implementing an IS model in this step in order to analyze the collected data by applying IS analysis. The results of IS analysis indicated which area the quality factors belong to. These results of IS analysis were also used as the domain knowledge which assists IS-DT feature selection methods in the study. These sub-steps are listed as follows.

- Step 5.1: Compute the mean values of importance and satisfaction for individual quality factors;
- Step 5.2: Compute the overall mean values of importance and satisfaction;
- Step 5.3: Categorize the quality factors into the IS model;
- Step 5.4: Give scores for different IS categories. The IS categories and their corresponding scores are displayed in Table 1.
Table 1. Scores for each IS category.

| IS Categories     | Score |
|-------------------|-------|
| Excellent zone    | 4     |
| To-be-improved zone | 3     |
| Surplus zone      | 2     |
| Care-free zone    | 1     |

Step 6: Construct decision trees (DT).

Two class label, “customer satisfaction” and “customer loyalty”, were present in our collected data. For each class label, we built decision trees, respectively, to discover different feature sets for customer satisfaction and customer loyalty.

Step 6.1: Use a 5-fold cross validation experiment and build a DT for each fold of data. In other words, the data set was divided into five equal-sized sets and each set was then in turn used as the test set.

Step 6.2: Compute the occurrence frequency of features in nodes.

Step 6.3: Pick a tree whose performance is the best and rank features by its attribute usage.

Step 6.4: Give scores according to the percentage of attribute usage of training cases for which the value of that attribute is known and is used in predicting a class. For instance, if one attribute’s usage value is 18%, it means that the DT uses a known value when classifying 18% of the training cases. The corresponding scores and their intervals of attribute usage are shown in Table 2.

Table 2. Scores for different intervals of attribute usage.

| Attribute Usage | Score |
|-----------------|-------|
| 75–100%         | 4     |
| 50–75%          | 3     |
| 25–50%          | 2     |
| 0–25%           | 1     |

Step 7: Feature selection.

In this step, the score of the IS category was multiplied by the score of DT attribute usage as our base for feature selection. The feature whose score was larger than the average value of all elements was indicated as an important factor.

Step 8: Draw a conclusion.

Finally, we drew conclusions based on the results of Steps 5–7.

3.2. An Illustrative Example

To clarify our proposed IS-DT method, we provided an illustrative example as shown in Figure 3. In step 1, we reviewed the service quality elements of programmatic buying from the published literature. Take the factor “information” which was defined as “the website can safely, timely, and precisely provide customers the desired information” as an example. In step 2, based on this definition, a pair of questions about perceived importance and satisfaction were developed. The sample questions for the IS model can be found as follows.
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- **Perceived satisfaction question:** How would you feel about the performance of this factor “the website can safely, timely, and precisely provide customers the desired information”? (A) Very satisfied (B) Satisfied (C) Neutral (D) Dissatisfied (E) Very Dissatisfied

- **Perceived importance question:** Do you think the importance of this factor “the website can safely, timely, and precisely provide customers the desired information”? (A) Very important (B) Important (C) Neutral (D) Unimportant (E) Very Unimportant

After developing a complete questionnaire, we implemented a pilot test (about 10~20 respondents) to obtain related opinions for modifying our developed questionnaire. Then, we collected data from people who have experienced mobile shopping (Step 4). In Step 5, we conducted the IS analysis. The service quality element “information” was categorized into “excellent area” in the IS model. As shown in Table 1, the score of “information” in the IS model is 4.

We used “customer loyalty” as a class label. In Step 6, we built five decision trees (5-fold cross-validation experiment), and then selected one tree which had the best classification performance. Among five trees, we selected a tree that had the highest classification accuracy of 59.30%. In this tree, seven attributes were selected.

For example, the attribute usage of the service quality element “information” was 47%. Then, as shown in Table 2, the score of DT-based feature selection was 2. In Step 7, the IS score of 4 multiplied by the DT score of 2 was 8 which was larger than the average score of all elements (3.79). Thus, we concluded the feature “information” was an important service quality element for customer loyalty in Step 8.

**Figure 3.** Implemental procedure of the IS-DT proposed method.
3.3. Samplings

The samples of this research were people who have experienced programmatic buying. Out of the 298 online questionnaires distributed, 133 received responses were valid. The results of the questionnaire summarized in Table 3 indicated that 50.38% respondents were male; 52.63% were between 20 to 30; 28.57% were service workers; 22.56% were students; 15.79% worked in manufacturing sectors; 42.86% had TWD 20,000–40,000 monthly income; 54.14% shopped online 1–5 times in the past half year; 21.80% shopped online 6–10 times in the past half year; 12.78% purchased over 20 times through mobile shopping; 48.87% spent TWD 1000–3000 as the average purchase amount; 40.60% spent below TWD 1000 as the average purchase amount; 45.86% used mobile devices less than 3 h per day; and 30.83% used mobile devices 3–5 h daily.

Table 3. Descriptive statistics of the selected samples.

| Variables                        | Distribution                  |
|----------------------------------|-------------------------------|
| Gender                           | Male 50.38%                   |
|                                  | Female 49.62%                 |
| Age                              | Below 20 7.52%                |
|                                  | 20–30 52.63%                  |
|                                  | 31–40 31.58%                  |
|                                  | Above 41 8.27%                |
| Education                        | High school and below 18.80%  |
|                                  | Undergraduate 66.17%          |
|                                  | Graduate and above 15.04%     |
| Occupation                       | Self-employed 6.77%           |
|                                  | Service 28.57%                |
|                                  | Information 10.53%            |
|                                  | Manufacturing 15.79%          |
|                                  | Public servants 3.76%         |
|                                  | Students 22.56%               |
|                                  | Housewives 9.02%              |
|                                  | Others 3.01%                  |
| Income per month                 | Below TWD 20,000 36.84%       |
|                                  | TWD 20,000–40,000 42.86%     |
|                                  | TWD 40,000–60,000 15.79%     |
|                                  | Above TWD 60,000 4.51%        |
| Mobile shopping times in the past half year | None 2.26% |
|                                  | 1–5 times 54.14%              |
|                                  | 6–10 times 21.80%             |
|                                  | 11–20 times 9.02%             |
|                                  | Over 20 times 12.78%          |
| Average purchase amount          | Below TWD 1000 40.60%         |
|                                  | TWD 1000–3000 48.87%          |
|                                  | TWD 3000–6000 9.02%           |
|                                  | Above TWD 6000 1.50%          |
| Average time of using mobile devices per day | Below 3 h 45.86% |
|                                  | 3–5 h 30.83%                  |
|                                  | 5–7 h 9.02%                   |
|                                  | Above 7 h 14.29%              |

4. Implementation
4.1. Service Quality Factors of Programmatic Buying

After reviewing some related works listed in Table 4, we combined all mentioned service quality factors in the literature and defined 24 service quality factors and two class labels, “customer satisfaction” and “customer loyalty”, for further analysis. Table 3
summarizes the proposed factors, their definitions, and supported references. Moreover, based on respondents’ suggestions in the pilot step (Step 3), two factors, “QR code” and “personalized interface”, were added. Therefore, the proposed factors were divided into seven sub-factors to highlight the uniqueness of programmatic buying.

### Table 4. Service quality factors of programmatic buying.

| No. | Factor/Sub-Factor | Definition | References |
|-----|-------------------|------------|------------|
| 1.  | Attitude          | The website provides friendly services and its attitude shows me that mobile service providers (MSPs) understand customers’ needs. | Lu et al. [23]; Kuo and Yen [78] |
| 2.  | Expertise         | The website can answer my questions quickly and understand that customers can rely on its knowledge to meet their needs. | Lu et al. [23]; |
| 3.  | Problem solving   | When customers have problems, the MSPs can solve their problems or complaints directly and immediately. | Su et al. [28]; Ladhari [51]; Parasuraman et al. [79]; Bauer et al. [80] |
| 4.  | Information       | The website can safely, timely, and precisely provide me the desired information. | Wu and Wang [18]; Lu and Su [19]; Lu et al. [23]; Su et al. [28]; Ding et al. [29]; Ladhari [51]; Carlson and O’Cass [50] |
| 5.  | Equipment         | Customers can count on their mobile devices to successfully complete the entire trading process. Moreover, with different mobile devices, the MSPs can provide the same service. | Lu et al. [23] |
| 6.1 | Touch             | The design of the touch interface is user-friendly and easy to use. | Ladhari [51]; Bauer et al. [80]; Heim and Field [81] |
| 6.2 | Single column     | The website can have a simple and clear single-column design of web pages. | Carlson and O’Cass [50] |
| 6.3 | Button            | The website can provide a suitable size button to avoid touches by mistake. | Ding et al. [29] |
| 6.4 | Graphics          | Pictures/images are always displayed properly. | Su et al. [28] |
| 6.5 | Voice guidance    | The website can provide a voice guidance service during the process of shopping. | Lu et al. [23] |
| 6.6 | QR code           | The website can provide QR codes to help customers to obtain the desired information. | |
| 6.7 | Personalized interface | The website can provide a personalized interface according to customer mobile devices. | |
| 7.  | Situation         | The mobile telecommunications network can meet a customers’ needs. Moreover, if a customer is in confined environments, such as basements and elevators, he/she still can receive real-time information that the website provides. | Lu et al. [23] |
| 8.  | Punctuality       | When the security trading completes, the trading information is sent back in a timely fashion and the website can provide customized information. | Lu et al. [23] |
| 9.  | Tangibles         | During the course of security trading, the information-processing time is predictable and the MSPs deliver the information quickly. | Lu et al. [23] |
| 10. | Valence           | When the service completes, a customer usually feels that he had a good experience. | Lu et al. [23] |
Table 4. Cont.

| No. | Factor/Sub-Factor   | Definition                                                                 | References                                                                 |
|-----|--------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------------|
| 11  | Corporate image    | The website has a good reputation.                                        | Lu et al. [23]                                                            |
| 12  | Service            | The website can have a call center and provide online help functions, comparison information about shopping, and good post-purchase services. | Wu and Wang [18]; Lu and Su [19]                                           |
| 13  | Promotion          | The website can provide promotional activities.                           | Wu and Wang [18]; Lu and Su [19]                                           |
| 14  | Convenience        | It is easy to find what a customer needs and customers can have a quick response time on the website. In addition, the website can provide personalized shopping information, multiple payment alternatives, a reasonable delivery time, order tracking and status query functions. | Wu and Wang [18]; Lu and Su [19]; Su et al. [28]; Carlson and O’Cass [50]; Ladhari [51]; Parasuraman et al. [79]; Bauer et al. [80] |
| 15  | Assurance          | The website can have a refund or flawed-product return guarantee and assure transaction security. | Wu and Wang [18]; Lu and Su [19]; Su et al. [28]; Ladhari [51]; Parasuraman et al. [79]; Bauer et al. [80]; Heim and Field [81] |
| 16  | Entertainment      | Entertainment provided by the website can give customers fun when using this website and excitement when shopping. | Ladhari [51]; Bauer et al. [80]                                             |
| 17  | Ease of use        | The website can direct customers step by step. Only a few clicks are needed to get what they want. When using the website, the customer also has full control at all times. | Su et al. [28]; Carlson and O’Cass [50]; Ladhari [51]; Parasuraman et al. [79]; Bauer et al. [80] |
| 18  | Safety             | This website protects customers’ personal information and the information about web-shopping behavior. | Su et al. [28]; Carlson and O’Cass [50]; Ladhari [51]; Parasuraman et al. [79]; Bauer et al. [80] |
| 19  | Satisfaction       | I am satisfied with my decision to purchase from this website.            | Ding et al. [29]; Anderson and Srinivasan [82]                             |
| 20  | Loyalty            | When I need to make a purchase, this website is my first choice. I seldom consider shifting to another website. | Ding et al. [29]; Parasuraman et al. [79]; Anderson and Srinivasan [82]     |

4.2. Research Results

4.2.1. Results of Importance–Satisfaction Model (IS Model)

The results reported that in Taiwan, the three top frequently used shopping sites were Yahoo (81.20%), PChome (43.61%), and Ruten (32.33%). The frequently utilized mobile devices were “smart phones (70.68%)”, “laptop PC (42.86%)”, and “tablet PC (36.84%)”. The frequently purchased products via mobile shopping were “costume and accessories (58.65%)”, “3C products (49.62%)”, “articles of daily use (33.83%)”, “purses (32.33%)”, and “cosmetics (32.33%)”. The most used payment method was credit card (45.86%).

All the service quality factors were placed in the IS model. As shown in Table 5, the nine factors and sub-factors in the excellent area (area I) were “problem solving”, “information”, “single column”, “voice guidance”, “QR code”, “situation”, “assurance”, “entertainment”, and “safety”. It can be concluded that customers highly needed these
services and felt satisfied with these provided services. These results also show that these service factors can be used to retain loyal customers effectively.

### Table 5. Results of the IS model.

| No. | Factor               | No. | Sub-Factor          | Category of IS Model |
|-----|----------------------|-----|---------------------|----------------------|
| 1.  | Attitude             | 6.1 | Touch               | S (42.1%)            |
| 2.  | Expertise            | 6.2 | Single column       | E (54.8%)            |
| 3.  | Problem solving      | 6.3 | Button              | S (45.8%)            |
| 4.  | Information          | 6.4 | Graphical           | S (45.1%)            |
| 5.  | Equipment            | 6.5 | Voice guidance      | E (40.6%)            |
| 6.  | Design               | 6.6 | QR code             | E (42.8%)            |
| 7.  | Situation            | 6.7 | Personalized interface | S (40.6%)  |
| 8.  | Punctuality          |     |                     | E (50.3%)            |
| 9.  | Tangibles            |     |                     | S (43.6%)            |
| 10. | Valence              |     |                     | C (50.3%)            |
| 11. | Corporate image      |     |                     | S (41.3%)            |
| 12. | Service              | 11. |                     | C (48.1%)            |
| 13. | Promotion            | N/A |                     | S (37.5%)            |
| 14. | Convenience          |     |                     | S (37.5%)            |
| 15. | Assurance            |     |                     | E (42.1%)            |
| 16. | Entertainment        |     |                     | E (46.6%)            |
| 17. | Ease of use          |     |                     | S (45.1%)            |
| 18. | Safety               |     |                     | E (45.8%)            |

Note: S = Surplus, E = Excellent, C = Carefree.

A total of 11 service factors and sub-factors in the surplus area (area II) included “attitude”, “expertise”, “equipment”, “touch”, “button”, “graphical”, “personalized interface”, “valence”, “promotion”, “convenience”, and “ease of use”. It can be indicated that service demand was below the average score (3.79), and the customers were not concerned with these services. Service satisfaction was higher than the average score, indicating that these resources were not placed in the right position or were being wasted. Thus, these surplus resources should be relocated to service factors with high demand and low satisfaction. The remaining factors were considered carefree elements.

#### 4.2.2. Results of Decision Tree Model (DT Model)

Table 6 summarizes the results of the 5-fold cross-validation experiment by the DT model. For “loyalty”, fold 3 has the best performance (59.30%). For “satisfaction”, the performance of fold 4 outperformed the others (76.9%). Therefore, two trees containing all appeared distributions in these folds were selected for feature selection.
Table 6. Results of fivefold cross-validation experiments in the DT model.

| Experiment     | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5 | Mean | Standard Deviation |
|----------------|--------|--------|--------|--------|--------|------|-------------------|
| Overall accuracy | 44.40% | 48.10% | 59.30% | 53.80% | 53.80% | 51.88% | 5.76%             |
| Loyalty        | 63.00% | 59.30% | 66.70% | 76.9%  | 65.4%  | 66.26% | 6.58%             |

Table 7 lists all attributes appearing in these two trees and their top-down rankings in accordance with the percentage of the attribute usage of every feature.

Table 7. The selected factors by decision tree model.

| No. | Extracted Factor/Sub-Factor | Attribute Usage | No. | Extracted Factor/Sub-Factor | Attribute Usage |
|-----|------------------------------|-----------------|-----|------------------------------|----------------|
| 9   | Tangibles                    | 100%            | 2   | Expertise                    | 100%           |
| 17  | Ease of use                  | 100%            | 9   | Tangibles                    | 100%           |
| 3   | Problem solving              | 97%             | 4   | Information                  | 47%            |
| 10  | Valence                      | 59%             | 15  | Assurance                    | 47%            |
| 8   | Punctuality                  | 50%             | 1   | Attitude                     | 33%            |
| 1   | Attitude                     | 41%             | 6.6 | QR code                      | 25%            |
| 11  | Corporate image              | 41%             | 16  | Entertainment                | 25%            |
| 13  | Promotion                    | 39%             |     |                              |                |
| 6.1 | Touch                        | 8%              |     |                              |                |
| 6.3 | Single column                | 7%              |     |                              |                |

4.2.3. Results of Importance–Satisfaction and Decision Tree Model (IS-DT Model)

Table 8 reports our IS-DT feature selection method. All factors whose multiplication score was above the average value (3.79) were selected. Therefore, the total of 11 selected factors for improving customer loyalty were “expertise”, “problem solving”, “information”, “single column”, “voice guidance”, “QR code”, “situation”, “tangibles”, “assurance”, “entertainment”, and “safety”. For increasing customer satisfaction, the four crucial attributes were “problem solving”, “punctuality”, “valence”, and “ease of use”.

Table 8. Results of the IS-DT feature selection method.

| No. | IS-DT | Score | Loyalty | Satisfaction |
|-----|-------|-------|---------|--------------|
|     | Attribute Usage | Score | Multiplication | Selection | Attribute Usage | Score | Multiplication | Selection |
| 1.  | S     | 2     | 33%      | 2           | 4           | 41%   | 2               | 4           |
| 2.  | S     | 2     | 100%     | 4           | 8           | X     | 0%              | 1           | 2           |
| 3.  | E     | 4     | 0%       | 1           | 4           | X     | 97%             | 4           | 16          | X           |
| 4.  | E     | 4     | 47%      | 2           | 8           | X     | 0%              | 1           | 4           |
| 5.  | S     | 2     | 0%       | 1           | 2           | 0%    | 1               | 2           |
| 6.1 | S     | 2     | 0%       | 1           | 2           | 8%    | 1               | 2           |
| 6.2 | E     | 4     | 0%       | 1           | 4           | X     | 7%              | 1           | 4           |
| 6.3 | S     | 2     | 0%       | 1           | 2           | 0%    | 1               | 2           |
| 6.4 | S     | 2     | 0%       | 1           | 2           | 0%    | 1               | 2           |
Table 8. Cont.

| No. | IS-DT | Score | Loyalty | Satisfaction |
|-----|-------|-------|---------|--------------|
|     |       |       | Attribute Usage | Score | Multiplication | Selection | Attribute Usage | Score | Multiplication | Selection |
| 6.5 | E     | 4     | 0%       | 1     | 4             | X         | 0%       | 1     | 4             |          |
| 6.6 | E     | 4     | 25%      | 2     | 8             | X         | 0%       | 1     | 4             |          |
| 6.7 | S     | 2     | 0%       | 1     | 2             | X         | 0%       | 1     | 4             |          |
| 7.  | E     | 4     | 0%       | 1     | 4             | X         | 0%       | 1     | 4             |          |
| 8.  | S     | 2     | 0%       | 1     | 2             | X         | 50%      | 3     | 6             | X        |
| 9.  | C     | 1     | 100%     | 4     | 4             | X         | 100%     | 4     | 4             |          |
| 10. | S     | 2     | 0%       | 1     | 2             | X         | 59%      | 3     | 6             | X        |
| 11. | C     | 1     | 0%       | 1     | 1             | X         | 41%      | 2     | 2             |          |
| 12. | S     | 2     | 0%       | 1     | 2             | X         | 0%       | 1     | 2             |          |
| 13. | S     | 2     | 0%       | 1     | 2             | X         | 39%      | 2     | 4             |          |
| 14. | S     | 2     | 0%       | 1     | 2             | X         | 0%       | 1     | 2             |          |
| 15. | E     | 4     | 47%      | 2     | 8             | X         | 0%       | 1     | 4             |          |
| 16. | E     | 4     | 25%      | 2     | 8             | X         | 0%       | 1     | 4             |          |
| 17. | S     | 2     | 0%       | 1     | 2             | X         | 100%     | 4     | 8             | X        |
| 18. | E     | 4     | 0%       | 1     | 4             | X         | 0%       | 1     | 4             |          |
|     | Average |       | 3.80     |       |               |           | Average | 4.08            |          |

Note: S = Surplus, E = Excellent, C = Carefree.

5. Discussions

Table 9 compares the extracted factors associated with customer loyalty and customer satisfaction. From this table, it was obvious that customer satisfaction was directly affected by “problem solving”, “punctuality”, “valence” and “ease of use” which could be considered as basic requirements of programmatic-buying services. In contrast, for customer loyalty, the acquired factors were focused on professional requirements in a programmatic buying environment. For example, the factors “expertise”, “problem solving”, “information”, and “tangibles” indicated the professional skills, such as the ability and knowledge of answering customers’ questions, solving customers’ problems or complaints directly and immediately; providing the desired information precisely, and delivering the transaction information quickly and predictably, which were significant for maintaining customer loyalty. The factors “single column”, “voice guidance”, and “QR code” were specialized designs for mobile devices. “Entertainment” was another unique factor in the programmatic-buying sector in which PB providers should offer customers exciting online shopping environments. The other two factors “assurance” and “safety” were in high demand. “Assurance” means that the service providers should have a refund or flawed-product return guarantee and assure transaction security. Likewise, “safety” was significant because of the growing tendency for unstable security in wireless environments. Therefore, customers’ personal information protection must be in high demand in M-shopping environments.
6. Conclusions

6.1. Concluding Remarks

In short, this study proposed a new IS-DT feature selection method to identify critical service quality factors for customer loyalty and satisfaction in mobile shopping. Our model not only can identify the important factors of mobile shopping, but also integrate domain knowledge during the process of selecting important attributes. The experimental results indicated that we successfully identified unique service quality factors in programmatic buying.

In our research, the features: “expertise”, “problem solving”, “information”, “single column”, “voice guidance”, “QR code”, “situation”, “tangibles”, “assurance”, “entertainment”, and “safety” have been identified as important features for increasing customer loyalty. This is especially true for some unique functions or settings for mobile devices, for example, “situation”, entertainment, and design factors including “single column”, “voice guidance”, and “QR code” which directly influence customer loyalty. In addition, “safety” and “entertainment” are critical factors in M-shopping. Other general factors, such as “expertise”, “problem solving”, “information”, “tangibles”, and “assurance” can be considered to be fundamental factors. The results of this study suggest that PB providers should focus on three major facilities in order to increase the customer loyalty. First, the PB providers should design M-shopping applications to be tailor-made for mobile devices. Second, the design quality of the interface should be enhanced regularly. Finally, M-shopping applications should not affect other resources of mobile devices and/or reduce the web-browsing speed.

From the empirical analysis, it was found that four service factors including “problem solving”, “punctuality”, “valence”, and “ease of use” were at high satisfaction levels. These factors could be considered basic factors which M-shopping service providers should take into consideration. Among these four factors, the “ease of use” of the website means that the layout of mobile apps should be light and easy to operate so that consumers can quickly complete the transactions they want to execute. After such a satisfactory purchase experience, consumers will be able to revisit this online store again. It is worth noting that “problem solving” is the factor that consumers care about most in terms of loyalty and satisfaction. This finding means that if PB providers can respond to complaints and questions sincerely and immediately, then consumers can be confident in the level of service provided by the website. Therefore, this study recommends that PB providers, based on practical problem-solving needs, conduct systematic research to effectively solve problems.

6.2. Future Research and Limitations

Discovering the relationship between service quality factors might represent a potential future study on mobile shopping. In addition, the other intermediate constructs, such as price, customer experience, and customer engagement may be considered for future research. The structural equation modelling (SEM) approach can also be utilized by using the software SmartPLS for evaluating our critical factors. Furthermore, we used the total score

Table 9. Factor comparison between loyalty and satisfaction.

| No. | Loyalty          | No. | Satisfaction    |
|-----|------------------|-----|-----------------|
| 2   | Expertise       | 3   | Problem solving |
| 3   | Problem solving | 8   | Punctuality     |
| 4   | Information     | 10  | Valence         |
| 6.2 | Single column   | 17  | Ease of use     |
| 6.5 | Voice guidance  |     |                 |
| 6.6 | QR code         |     |                 |
| 9   | Tangibles       |     |                 |
| 15  | Assurance       |     |                 |
| 16  | Entertainment   |     |                 |
| 18  | Safety          |     |                 |
of the IS-DT models as the product of the IS model and the DT model separately. Future researchers can try different combinations rather than products. Concerning samples, the main purpose of this study is to propose a feature selection method that integrates domain knowledge and apply it to PB. We recommend including a larger sample size in future studies to draw general conclusions.

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