An exploratory analysis of internet banking adoption using decision tree induction

Samer Takieddine and Francis Kofi Andoh-Baidoo*

Department of Computer Information Systems, University of Texas-Pan American, 1201 W University Drive, Edinburg, TX 78539, USA
E-mail: stakieddine@utpa.edu
E-mail: andohbaidoof@utpa.edu
*Corresponding author

Abstract: Although internet banking promises several benefits to bank customers, the adoption of online banking services continue to be low especially in developing countries. Prior research has examined internet banking adoption as a classification problem with a focus on adopters and non-adopters using traditional statistical approaches. In this paper we extend the problem by including partial adopters and used decision tree induction as the analytical method. Our results on data from customers in 20 countries show that household income is the most important variable in separating those who do not adopt IB or partially adopt IB from those who fully do. Education and age are the most important variables in separating partial adopters from non-adopters. While exploratory, our results provide opportunities for further theory development on internet banking adoption while practically contributing to discussions on how practitioners can develop specific strategies to targeted customers to become fully adopters of online banking services.

Keywords: e-finance; internet banking; internet banking adopters; decision tree; data mining; TAM; technology acceptance model; security; internet banking adoption.


Biographical notes: Samer Takieddine is an instructor and PhD student in Computer Information Systems and Quantitative Methods at the University of Texas – Pan American. His research interests include technology adoption, information security, social media, and application of data mining.

Francis Kofi Andoh-Baidoo is an Assistant Professor of Computer Information Systems at the University of Texas – Pan American. He has a PhD in Information Systems from the Virginia Commonwealth University at Richmond. His research interests include information security and privacy, knowledge management, decision support systems and application of data mining. He serves on the editorial board of five information systems journals. His research has appeared in journals such as Expert Systems with Applications,
1 Introduction

Traditional branch-based banking is the most common method for conducting banking transactions in the world (Wang et al., 2003). However, rapid diffusion of the internet has transformed business processes including the design and delivery of banking services (Nath et al., 2001; Khasawneh et al., 2009). For the last two decades, most banks all over the world have introduced internet banking (IB) services to improve their operations and to reduce costs (Tan and Teo, 2000; Nath et al., 2001; Andoh-Baidoo et al., 2010). Despite all the efforts by researchers and practitioners to encourage consumers to adopt online banking services and marketing IB as an easier and more convenient method to bank, IB remains underused by consumers. In 2013, only 4% of Romanians, 5% of Bulgarians, 11% of Turks and Greeks, 22% of Italians, and 23% of Croatians and Portuguese used internet to conduct banking transactions (Eurostat, 2013). This observation demands more research to understand consumers’ acceptance of IB.

There is a growing body of research that has examined the determinants and barriers to the adoption of IB services (Lee, 2009; Pikkarainen et al., 2004; Poon, 2007; Sadeghi and Farokhian, 2010; Sathye, 1999; White and Nteli, 2004). These studies relied on IB user samples or nonuser samples. In addition, some researchers compared the two samples (Gounaris and Kortos, 2008; Hernandez and Mazzon, 2007; Lee et al., 2005; Polasik and Wisniewski, 2009). Using both samples helped these studies profile consumers and segment them into IB adopters and non-adopters based on demographic data (e.g., age, education) and other independent variables. Profiling would help practitioners (banks) to design their offerings to specific target groups of customers.

The IB adoption is a classification problem requiring researchers to classify banking customers. Previous studies focused on adopters and non-adopters (Gerrard and Cunningham, 2003; Littler and Melanthiou, 2006; Ozdemir et al., 2008; Patsiotis et al., 2012; Rotchanakitumnuai and Speece, 2003). Further some studies have focused on non-adopters by segmenting non-adopters into two profiles. For example, Lee et al., (2005) segmented the non-adopters into ‘persistent non-adopters’ and ‘prospective adopters’ arguing that it is inaccurate and inappropriate to describe all non-adopters as a homogeneous population. Also, Hernandez and Mazzon (2007) segmented non-adopters into internet users and internet non-users. To our knowledge no previous study in the IB literature segmented adopters into more than one group. IB is both an informational medium and a transactional medium (Tan and Teo, 2000). Due to security concerns, some IB adopters might prefer to not risk conducting monetary transactions (e.g., pay bills, transfer funds) and use IB only as an informational medium (e.g., check balance, historic records, etc.). We contend that not all IB adopters use internet banking for both
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informational and transactional purposes. Therefore, in this paper we segmented IB adopters into full adopters for customers who use IB for both informational and transactional purposes, and partial adopters for customers who use IB for only informational purposes.

Studies that used both samples of IB adopters and non-adopters applied logistic regression as their statistical technique to develop profile of potential IB adopters (Lee et al., 2005; Hernandez and Mazzon, 2007; Gounaris and Kortos, 2008; Polasik and Wisniewski, 2009). Data mining techniques such as decision tree (DT) have been found to be better and more accurate predictors and classification methods than logistic regression (Delen et al., 2005; Zekic-Susac et al., 2004). Further the use of data mining techniques may provide new insights beyond what traditional statistical approaches such as logistic regression present (Andoh-Baidoo et al., 2013; Delen et al., 2005; Osei-Bryson and Ngwenyama, 2011). However, to our knowledge no previous study applied data mining techniques in studying IB adoption. DT is a powerful classification algorithm that has been used to develop theoretical models in the information systems discipline. For instance, DT induction has been employed to develop theoretical models for examining ERP systems and end-user performance (e.g., Delen et al., 2009; Kositanurit et al., 2011). Further, DT induction has been used to examine investors’ response to internet security breach (Andoh-Baidoo, 2013; Andoh-Baidoo et al., 2010) and Electronic Commerce (Andoh-Baidoo et al., 2012, 2013) announcements. In this paper, we use DT to profile IB full adopters, partial adopters, and non-adopters, and identify the most important predictive factors of IB adoption.

This paper makes contribution to both research and practice. For research, we present the first study, to our knowledge, that segments the banking consumers into three – IB full adopters, IB partial adopters, and IB non-adopters. Moreover, this is the first paper to our knowledge that applies DT, a data mining technique, as the statistical approach within the IB adoption literature. DT helped us identify the most important variables that differentiate banking consumers within the three segments of IB adoption (Full, partial, and non). The DT provides new insights. For instance, unusual to findings from previous IB adoption empirical studies (Lee et al., 2005; Polasik and Wisniewski, 2009; Patsiotis et al., 2012), our study found demographic variables to be more important than consumers’ perceptual variables such as perceived ease of use, perceived usefulness, and perceived security. This should encourage IS researchers in general and IB adoption researchers in particular to apply data mining techniques for better explanation of the IB adoption phenomenon and more robust findings.

The paper contributes to practice in that our study’s findings provide useful information that could be used to develop effective IB marketing strategy to focus on using their customers’ demographic data to identify potential IB adopters. Moreover, banks’ management can promote more transactional IB services (e.g., transfer money between different accounts, pay credit cards, pay bills, manage their stocks and loans) for the customers who are IB partial adopters, that is, who use IB only as an informational medium. In this case, banks will be able to increase the number of IB adopters within their customers in general and the full adopters in particular on a faster pace. Also, using the demographic segmentation will help banks to decrease their time and cost of their IB marketing campaigns and thereby improve efficiencies. Increasing the number of IB adopters within banks’ customers could generate higher profit and less operational expenses.
The rest of the paper is organised as follows. We first review the relevant literature including IB advantages, technology acceptance model (TAM) theory, and DT. In the subsequent section, we describe our study’s methodology including data collection and decision tree’s application. The next section includes the results, and the final section includes the conclusion, limitations, and potential future research.

2 Theoretical background

We present the theoretical background of the research. Specifically, we discuss relevant research including the benefits of IB. We also discuss TAM with a focus on its application to IB. In addition we discuss the importance of including perceived security as one of the constructs in our research model.

2.1 Internet banking advantages

A critical business model for the survival of banks is IB because the number of internet users as well as IB users in the world is growing very fast (Eurostat, 2013). IB helps banks to improve their customer services and customer satisfaction. It provides customers with an easy access to their banking information and allows them to perform financial transactions 24/7 at their own convenience (Dawes and Rowley, 1998; Tan and Teo, 2000). Also, banks that offer IB services gain competitive advantages (e.g., Rexha et al., 2003; Andoh-Baidoo et al., 2010) over brick and mortar banks because they would attract a new segment of consumers represented by the e-commerce adopters. Such competitive advantage can be mostly achieved in developing countries such as Vietnam and Sudan where internet banking is still at the infancy stage (Alam et al., 2010; Chong et al., 2010).

Furthermore, banks that offer IB services are able to decrease their costs and increase their profits (Yang and Ahmed, 2009). For example, the average transaction cost at a physical bank branch is $1.07, while the same transaction conducted at a bank’s website costs the bank only one cent (Nath et al., 2001; Kirlidog and Kaynak, 2011). Also, the cost of operating IB is 40% less than that of a physical branch (Nath et al., 2001; Tan and Teo, 2000). Moreover, with the increase in IB use, banks do not need as much physical branches as they used to, for example in 2009, Bank of America closed approximately 10% of its branches (600 locations) in the USA (IB, 2009).

2.2 Technology acceptance model (TAM)

TAM is a mature model that has been used by researches since it was presented by Davis (1989) to study potential adoptions of technology products and services. The importance of TAM in predicting and explaining use is represented by the perceived usefulness and perceived ease of use, which are two theoretical constructs that form the basic determinants of system use (Davis, 1989).

The perceived usefulness of a technology product or service is the degree to which a potential adopter trusts that using it will improve his/her job performance. The perceived ease of use is the degree to which he or she believes that using it would be free of difficulty (Davis, 1989). In the case of IB adoption, perceived usefulness is measured by the degree to which customers believe that IB is more advantageous compared to traditional banking (Chong et al., 2010). This includes serving customers’ needs similarly
to what they used to get in a physical branch with no or limited errors and saving time and money compared to the disturbance and cost of visiting traditional bank (Gao and Owolabi, 2008; Rao et al., 2003). On the other hand, the perceived ease of use is explained in IB by how easy it is for customers to surf the bank’s website through finding the web pages that contain the information customers are looking for. IB also allows customers to perform all the basic and common transactional banking tasks such as transferring money and paying bills.

Between 1992 and 2003, approximately 100 empirical studies were conducted on technology adoption by individuals and organisations; perceived usefulness and perceived ease of use were the top two independent variables used in researches, 29 times and 27 times respectively (Jeyaraj et al., 2006). However, prior literature shows that TAM alone is not enough to understand or explain the adoption of technology products and services (Chong et al., 2010; Straub et al., 1997). Thus, other variables such as perceived security have been added to TAM in previous studies to gain a better understanding of the adoption of technology products (Hernandez and Mazzon, 2007; Jahangir and Begum, 2008).

2.3 Perceived security

It has been found that consumers’ security concerns are a major obstacle to e-commerce adoption in general and IB adoption in particular (Khasawneh et al., 2009). If security is improved customers are willing to bank over the internet (Lee, 2009; Liao and Wong, 2008; Mansumitrchai and AL-Malkawi, 2011; Pikkarainen et al., 2004; Poon, 2007; Rasolinezhad, 2009; Sadeghi and Farokhian, 2010; Sathye, 1999; Tan and Teo, 2000).

Yenisey et al. (2005) defined perceived security as the extent of security users feel while conducting online activities (e.g., shopping, banking) on e-commerce websites. This extent of security was clearly explained in Flavian and Guinaliu (2006)’s definition of perceived security – “the subjective probability with which consumers believe that their personal information (private and monetary) will not be viewed, stored, and manipulated during transit and storage by inappropriate parties in a manner consistent with their confident expectations” [p.604]. Personal information involved in online banking activities do not only include private personal information as it is the case with most online activities (e.g., email, social networks), but they also include monetary information. This might make some consumers more sensitive about IB security because if their personal information is viewed, stored, or manipulated, then the consequences are not simply related to privacy breach, but also potential financial losses. Therefore, consumers’ security perception in IB can be more critical than other online activities.

Perceived security has been approached in two different ways by prior studies. For example, Lallmahamood (2007) and Wang et al. (2003) used perceived security by referring to consumers’ perception of protection against security threats and control of their personal information online. On the other hand, Chen and Barnes (2007) explained perceived security as threats that cause destruction or disclosures to data or network resources by modifying data, causing denial of service, and committing fraud. In this paper, we used perceived security as a general term of security that reflects consumers’ general perception of how secured their information is in the online banking environment.
Based on what was proposed above, we adopted a research model, Figure 1, which has been suggested by previous IB adoption publications (Lallmahamood, 2007; Lee, 2009; Liao and Wong, 2008; Mansumitchai and Al-Malkawi, 2011; Pikkarainen et al., 2004; Poon, 2007; Rasolinezhad, 2009; Sadeghi and Farokhian, 2010; Sathy, 1999; Tan and Teo, 2000).

Figure 1  Internet banking adoption model

2.4 Decision tree

DT is a data mining technique. It uses a set of classification algorithms that are becoming more popular in the field of information systems (Delen et al., 2005). DT represents a decision problem that takes the structure of an inverse of a tree with the root at the top and leaves at the bottom. In this tree, every non-leaf node is connected with one of the decision variables, and every branch from a non-leaf node is connected with sub-values of the equivalent decision variable, and each leaf node is connected with a value of the dependent variable. If the dependent variable also called target variable is discrete then the DT induction is considered to be a classification tree and for each node the DT generation algorithm generates the relative probabilities for each class of the dependent variable. At every leaf a class is assigned, where the class that provides the largest class probability is the winning class. DT identifies the most significant variables in predicting the decision outcome. The most significant variable is located at the root of the tree and succeeding variables further discriminate between the decision outcomes (Andoh-Baidoo, 2013). The series of variables and their values in DT can be converted to the rules of an expert system. Such rules have excellent explanation power (Quinlan, 1990).

The DT technique separates observations in branches to build a tree for improving the prediction accuracy. This technique includes several mathematical algorithms such as information gain, Gini index, and Chi-squared test to identify the corresponding threshold for each variable that splits the observations into several subgroups (Delen et al., 2005). Each variable creates a leaf node that splits into two or more groups. The purpose of the splitting algorithm is to maximise the homogeneity of the resulting two or more subgroups of samples.

3 Research methodology

In this study, we used a convenience snowball sampling technique to collect our data. This sampling technique has been employed in several previous e-banking studies as it facilitates reaching banks customers and collecting their information while banks do not allow disclosing their customers’ information (Casalo et al., 2008; Rootman et al., 2011;
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Yuen, 2013). The survey questionnaire was posted on Facebook. Facebook users were recruited by posting an e-invitation to participate that includes the topic and its purpose. Participants were encouraged to share the posting with their friends and family by publishing our survey on their Facebook accounts. Participation was limited to individuals who are 18 years or older and are bank customers, hereafter referred to as customers. We got responses from Canada, Czech Republic, Germany, Japan, Lebanon, Mexico, Palestine, Qatar, Saudi Arabia, Serbia, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, UAE, UK, USA, and Vietnam. The distribution of respondents by geographic regions is as follows: Asia (32.4%), Europe (17.1%), and North America (50.5%).

The survey was developed based on previous e-commerce studies, IB, and information technology security literature. The questions selected for the constructs are adopted from Chen and Barns (2007), Pavlou (2003), Salisbury et al. (2001), and Lallmahamood (2007) as shown in Table 1.

<table>
<thead>
<tr>
<th>Content</th>
<th>Source of survey items</th>
</tr>
</thead>
</table>

The dataset included one target variable (IB adoption), and nine input variables represented by perceived security, perceived ease of use, perceived usefulness, education, age, status, household income, internet experience, and computer experience. For our target variable, we used IB adoption with the following three values: “1 for partial adopters”, “2 for full adopters”, and “3 for non-adopters”. The survey questions were of two types, demographic questions and 5-point Likert scale questions (1 strongly disagree – 5 strongly agree). Education was categorically scored following these values: “1 for 12th grade or less”, “2 for Graduated high school or equivalent”, “3 for Some college, no degree”, “4 for Bachelor degree”, and “5 for Master’s degree or higher”. Also, household income was scored “1 for Less than $12,000”, “2 for $12,000 to $23,999”, “3 for $24,000 to $35,999”, “4 for $36,000 to $47,999”, “5 for $48,000 to $59,999”, “6 for $60,000 to $74,999”, “7 for $75,000 to $99,999”, and “8 for $100,000 or more”. The survey questions are reported in Appendix A.

We discretised the ‘Education’ and ‘Household Income’ variables following Osei-Bryson and Ngwenyama (2011) recommendation to use discrete ordinal variables instead of using intervals, which is important for our systematic analysis. Table 2 shows the discretised qualitative and numeric intervals for each category.

We used SPSS 22 application to generate the DT using Gini index algorithm found in the CART decision tree method. Our final data sample is 298 observations including 62 partial adopters, 167 full adopters, and 69 non-adopters. However, we only used 186 to maintain equal groups of 62 observations for each type of IB adoption including non-adopters, partial adopters, and full adopters, otherwise our sample would have been skewed towards full adopters which would make our findings biased. In DT application, matching the number of observations or cases between different groups of data sample was applied in prior studies (Kirkos et al., 2007). To make sure that the 62 full adopters
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we used in our final sample are not different than the full adopters observations that we disregarded, we applied One-Way ANOVA to compare between both samples. Table 3 shows that there was no significant difference (at \( P < 0.05 \)) between the two full adopters samples.

### Table 2 Demographic variables discretisation

<table>
<thead>
<tr>
<th>Category</th>
<th>Qualitative</th>
<th>Numeric</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>12th grade or less</td>
<td>[1, 2]</td>
</tr>
<tr>
<td></td>
<td>Graduated high school or equivalent</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>Some college, no degree</td>
<td>[3, 4]</td>
</tr>
<tr>
<td></td>
<td>Bachelor degree</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Master’s degree or higher</td>
<td>[5]</td>
</tr>
<tr>
<td>Low</td>
<td>Less than $12,000</td>
<td>[1, 2]</td>
</tr>
<tr>
<td></td>
<td>$12,000 to $23,999</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>$24,000 to $35,999</td>
<td>[3, 4, 5]</td>
</tr>
<tr>
<td></td>
<td>$36,000 to $47,999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$48,000 to $59,999</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>$60,000 to $74,999</td>
<td>[6, 7, 8]</td>
</tr>
<tr>
<td></td>
<td>$75,000 to $99,999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$100,000 or more</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3 One-way ANOVA test on the full adopters samples

<table>
<thead>
<tr>
<th></th>
<th>( F )-value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet experience</td>
<td>1.641</td>
<td>0.202</td>
</tr>
<tr>
<td>Computer experience</td>
<td>0.447</td>
<td>0.505</td>
</tr>
<tr>
<td>Gender</td>
<td>3.047</td>
<td>0.083</td>
</tr>
<tr>
<td>Status</td>
<td>1.488</td>
<td>0.224</td>
</tr>
<tr>
<td>Age</td>
<td>0.302</td>
<td>0.584</td>
</tr>
<tr>
<td>Education</td>
<td>0.02</td>
<td>0.887</td>
</tr>
<tr>
<td>Income</td>
<td>0.958</td>
<td>0.329</td>
</tr>
<tr>
<td>PU</td>
<td>0.386</td>
<td>0.535</td>
</tr>
<tr>
<td>PS</td>
<td>0.016</td>
<td>0.898</td>
</tr>
<tr>
<td>PEOU</td>
<td>0.509</td>
<td>0.476</td>
</tr>
</tbody>
</table>

To test the discriminant validity we used principal component analysis as the extraction method for factor analysis with Varimax rotation. As Appendix B shows, 80% of the variation in internet banking adoption is explained with excellent loading pattern of the three factors. To test the reliability of Perceived Usefulness, Perceived Ease of Use, and Perceived Security constructs we used Cronbach’s \( \alpha \). As Appendix B shows, all three constructs have Cronbach’s \( \alpha \) greater than 0.70, which make them reliable and acceptable to be used in our study (Nunnally, 1967).
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Similar to Education and Household Income, we discretised the factor scores for Perceived Usefulness, Perceived Ease of Use, and Perceived Security to achieve better systematic analysis (Osei-Bryson and Ngwenyama, 2011).

4 Results and discussion

Table 4 shows that the female respondents formed 53.8% of the total respondents. The age of the respondents ranged between 18 and 65 years old with a mean of 31.64 and standard deviation of 9.71, which makes the majority of our respondents’ age between 22 and 42 years old. More than a half of the respondents are single (53.8%).

Table 4  Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Range</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>IB adoption</td>
<td>186</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>2.00</td>
<td>0.819</td>
</tr>
<tr>
<td>Internet experience</td>
<td>186</td>
<td>27.0</td>
<td>0.0</td>
<td>27.0</td>
<td>11.812</td>
<td>4.8415</td>
</tr>
<tr>
<td>Computer experience</td>
<td>186</td>
<td>33.0</td>
<td>0.0</td>
<td>33.0</td>
<td>15.548</td>
<td>5.7657</td>
</tr>
<tr>
<td>Gender</td>
<td>186</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1.46</td>
<td>0.500</td>
</tr>
<tr>
<td>Status</td>
<td>186</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1.54</td>
<td>0.642</td>
</tr>
<tr>
<td>Age</td>
<td>186</td>
<td>47.0</td>
<td>18.0</td>
<td>65.0</td>
<td>31.640</td>
<td>9.7168</td>
</tr>
<tr>
<td>Valid N (listwise)</td>
<td>186</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5 shows that the largest group of respondents, 54.8% has medium education (Associate or Bachelor’s degree). The largest group of respondents, 43% has a medium annual household income ($24,000 and $59,999). The total respondents average internet and computer experience are 12 and 15 years respectively.

Table 5  Frequency

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>66</td>
<td>35.5</td>
</tr>
<tr>
<td>L</td>
<td>18</td>
<td>9.7</td>
</tr>
<tr>
<td>M</td>
<td>102</td>
<td>54.8</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>186</td>
<td>100</td>
</tr>
<tr>
<td><strong>Household income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>46</td>
<td>24.7</td>
</tr>
<tr>
<td>L</td>
<td>59</td>
<td>31.7</td>
</tr>
<tr>
<td>M</td>
<td>80</td>
<td>43</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>186</td>
<td>100</td>
</tr>
</tbody>
</table>

Our decision tree was able to classify partial adopters, full adopters, and non-adopters with an overall accuracy rate of 65.4%. The results of our decision tree model in Figure 2 shows the following classification rules of IB adoption:
1. If banks customers’ household income is high, they tend to fully adopt IB services.
2. If banks customers’ income is low or medium:
   a. If banks customers’ education is low, they tend to not adopt IB services.
   b. If banks customers’ education is medium or high:
      i. If banks customers’ age is greater than 32.5, they tend to not adopt IB services.
      ii. If banks customers’ age is equal to 32.5 or less, they tend to partially adopt IB services.

Figure 2  Decision tree model for IB adoption (see online version for colours)
Results show that IB non-adopters are customers who have low to medium household income, or/and low education, or/and age of more than 32.5 years old. Moreover, IB partial adopters are customers who have low to medium household income, or/and medium to high education, or/and younger age of 32.5 years old. And, IB full adopters are banks customers who have high household income.

Also, there is 100% probability that customers who do not have a high household income and have low education tend to fall under the IB non-adopters segment. However, there is 58% probability that banks customers who have low to medium household income and have medium to high education, and age more than 32.5 years old also would fall under the IB non-adopters segment. On the other hand, there is 58% likelihood that customers who age 32.5 or younger would fall under the IB partial adopters segment. Regarding the IB full adopters segment, the probability for banks customers falling within this segment would be 74% when those customers have high household income.

Based on what we presented above, we can conclude that household income is the main and major factor to identify IB full adopters. However, IB partial adopters and non-adopters can be identified using the following three factors, household income, education, and age.

In this paper we used the variable importance measure to judge the relative importance of each predictor variable. Surrogate splitting is used to rank the importance of the variables, with a relative importance measure scale for each predictor variable included in the analysis. The variable importance results are shown in Table 6.

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Importance</th>
<th>Normalised importance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>0.082</td>
<td>100.0</td>
</tr>
<tr>
<td>Education</td>
<td>0.071</td>
<td>87.2</td>
</tr>
<tr>
<td>Age</td>
<td>0.057</td>
<td>69.3</td>
</tr>
<tr>
<td>Computer experience</td>
<td>0.042</td>
<td>51.8</td>
</tr>
<tr>
<td>Internet experience</td>
<td>0.014</td>
<td>17.7</td>
</tr>
<tr>
<td>PU</td>
<td>0.009</td>
<td>10.9</td>
</tr>
</tbody>
</table>

Household income emerged as the most important variables. While household income is the most important variable in separating those who do not adopt IB or partially adopt IB from those who fully do, education and age emerged as the second and third most important variables. Further, education and age are the most important variables in separating those who partially adopt IB from those who reject or do not adopt it. The rest of the variables — computer experience, internet experience, and perceived usefulness — are the least important variables in our IB adoption DT model, while perceived ease of use, perceived security, status, and gender do not influence IB adoption in our model.

High household income is the best determinant of IB full adopters who use IB as a transactional medium to transfer money, pay bills, and manage their loans and other financial activities such as stocks management. We believe that households with high cash flow or/and more than one source of income most likely have several banking accounts like checking and saving accounts. This makes the probability of such customers having to transfer money among these different accounts more frequent than customers with low to medium household income. Also, with higher cash flow available,
people tend to invest their money in the stock market, which requires continuous management that can be conveniently and feasibly done using IB. Moreover, having a high household income would make their lifestyle more luxurious including having a big house with mortgage to pay, pool around the house with maintenance to keep, several cars with payments to fulfill every month, many types of insurance to purchase for the house (e.g., flood, fire, tornados, etc.) and cars, several credit cards to settle periodic bills. This makes IB their best friend to help managing all these financial activities with less time and effort possible.

On the other hand, we believe that customers with low to medium household income do not have many financial activities that require fully adopting IB or even use it at all. Most likely, if they adopt IB, they do it partially as an informational medium where they can monitor their account balance and plan their purchases accordingly instead of driving back and forth to the bank or ATM machine. Moreover, the lower customers’ education the higher the probability of them rejecting IB. Customers with low education and low household income tend to be less interested in using a computer and internet, or/and financially incapable of purchasing a computer and an internet service.

However, medium to high educated customers with low to medium household income that fall into the older generation (32.5 years old or higher) tend to reject and not adopt IB services. This can be explained that customers with low income have limited cash flow, which does not require much time and attention to manage. On the other hand, the younger group (32.5 years old or younger) of the educated customers with low to medium household income tend to partially adopt IB services, which make sense in comparison to the older generation because they are the Google and FaceBook generation (Critchell, 2012) who spend long hours online, which make them more likely to conduct online activities and in turn adopt and use most of e-services including IB. Not to forget, their limited household income would explain why they adopt IB partially and not fully as we explained earlier.

5 Implication to research and practice

This paper’s implications are two-fold, implications to research and to practice. Research wise this paper provides a new support for the fact that data mining techniques (e.g., DT) may provide new insights beyond what traditional statistical approaches such as logistic regression present. Here we learn about specific variables that are more important in classifying IB adopters and also the variables that are most important and the conditions under which a customer is fully adopter, partially adopter or completely non-adopter.

Second, previous IB empirical studies found that customers with more education and younger age should be the banks’ focus since the likelihood for them to adopt IB services is high (Hernandez and Mazzon, 2007). We argue that these findings are incomplete due to the fact that the IB adopters segment is not limited to one group only, instead our findings suggest two groups – full adopters and partial adopters – as well as the focus should not be limited to non-adopters only but should include partial adopters as well. Partial adopters who use IB only as an informational medium still cost banks money to conduct their financial transactions such as paying bills or rent, transferring money to other individuals (wire), purchase insurance, etc. Thus, our study presented new insights towards better understanding the IB adoption and use phenomenon that has not been proposed in prior IB empirical studies.
The paper contributes to practice as follows: first, even though prior studies found education and age as factors that impact the consumers’ decision to adopt or reject IB, our study’s findings help in profiling adopters from non-adopters, and the full adopters from partial adopters. Such profiling would help banks to use customers’ demographic information to segment and predict potential adopters and focus on educating non-adopters and partial adopters to fully use IB services. This will reduce marketing costs and improve the outcomes of their IB marketing campaign because instead of spending their resources on targeting all their customers, banks can save time and money targeting the non-adopters and partial adopters.

Second, management can target partial adopters who use IB only as an informational medium to promote transactional services (e.g., transfer money between different accounts, pay credit cards, pay bills, manage their stocks and loans, etc.). As a result, banks can achieve higher success rates of increasing the number of IB adopters within their customers in general and the full adopters within their IB users in particular. Increasing IB adopters within banks customers could generate higher profit and less operational expenses.

Third, we suggest some practical and beneficial directions for banks to follow to improve their customers’ acceptance of IB by executing the following strategy:

- To motivate customers who reject or do not use IB services, banks can offer the e-banking checking or/and saving account(s) option that requires customers to use IB instead of accessing a physical branch. To motivate customers into committing to using IB services, banks should provide financial incentives for them by eliminating all types of fees these customers used to pay monthly or annually for their regular checking or/and saving account(s). For example in the USA, a developed country, Bank of America offers such kind of promotions, where customers who switch or open an e-banking checking account can save the maintenance monthly fee of $8.95 (BoA, 2012). Also, banks can provide financial incentives to their customers by eliminating their monthly fees by requiring them to have their paychecks directly deposited in their checking or savings account. For example, Chase Bank customers can save a monthly service fee of $6 if they adopt the direct deposit service of at least $500 (Chase, 2013). Such incentives will definitely motivate IB non-adopters, to become partial adopters especially when our findings suggest that low to medium household income customers tend to not adopt IB services, which make those poor to middle class customers willing to save every dollar they can. In return, banks will reduce their physical branches’ operational expenses due to the decrease in the number of customers visiting the bank to conduct certain financial activities.

- To motivate customers to become IB full adopters instead of limiting their IB access and use to informational purposes. For that, we recommend banks to offer their customers credit card(s) with no annual fees, and cash back incentive towards their purchases (up to 5% cash back). Discover and Chase credit cards offer up to 5% cash back, Bank of America and American Express credit cards offer up to 3% cash back, while Citi and Capital One credit cards offer up to 2% cash back. Moreover, if those cash backs get deposited in the same bank’s checking account, customers gain extra 10% cash back by the end of the year (e.g., Chase bank and Bank of America). The same strategy and incentives can and do apply in the case of debit cards use, as well as an e-banking service called e-bill payment directly from the checking account. For example, Discover and Capital One banks both offer 10 cents cash back.
for every bill payment done using IB from the checking account. We believe that once customers get hooked into using IB as a transactional medium and experience its convenience managing and monitoring those additional financial activities, they will continue doing it and explore more IB services to reach the maximum possible IB services that can be relevant to them.

6 Conclusion

To our knowledge this paper is the first study that applies DT, a data mining technique, to examine the factors that impact consumers’ behaviours related to IB adoption. Moreover, using DT allowed our study to classify the factors based on their relative importance in identifying IB non-adopters from IB adopters, and IB partial adopters from IB full adopters. Household income is the major factor that distinguishes IB full adopters from the other two banks customers groups or segments. The results provided evidence confirming that consumers with high household income tend to fully adopt IB services. However, education and age were the major factors that distinguished partial adopters from non-adopters as the results showed that educated consumers who are 32.5 years old or younger tend to partially adopt IB services. They use the informational services available in the IB system such as checking their account balance. Nevertheless, it was observed that customers who are older than 32.5 years reject or do not use IB.

Furthermore, previous studies found perceived ease of use, perceived usefulness, and perceived security to have the major impact on consumers’ intentions to adopt IB. However, our study’s findings present the mentioned three constructs as less important factors than demographic factors and in particular household income, education and age. In 2013, we still found the IB adoption to be very low in developing countries such as Romania, Bulgaria, and Turkey (Eurostat, 2013). Therefore, this study presents practical and beneficial directions for practitioners like financial organisations and banks to execute a strategy that would make a difference by enhancing customers’ acceptance of IB services represented by its adoption.

Although, 65.4% predication accuracy is low; for an exploratory study this is a satisfactory accuracy value since lower values have been recorded in other studies (Mui and Fu, 1980; Zambon et al., 2006). Moreover, previous studies reported that accuracy varies with different splitting methods of data sample, the larger the training sample the more accuracy is achieved (Jonsdottir et al., 2008; Doyle et al., 2011). Good error estimates are difficult to achieve with small sample sizes (Jonsdottir et al., 2008). Therefore, future research can improve prediction accuracy with larger sample size.

A limitation of our study faced was the fact that we used 186 observations out of our 298 valid responses we received because of the disproportion in the response from IB non-adopters, partial adopters, and full adopters. Most of our respondents were IB adopters, and in particular full adopters. However, to maintain equal samples (62 observations) of those three customers’ groups we had to remove 112 observations, otherwise our findings would have been biased. Most likely our method of recruiting participants online, increased the probability of having educated respondents in general, and technology (computer and internet) oriented respondents in particular. Therefore, future studies should collect larger amount of respondents. Despite the noted limitations, the study is an exploratory analysis of IB adoption that demonstrates the potential of
applying DT approach to develop a theoretical model for explaining the adoption of IB. Addressing the limitations and providing more robust results is the focus of future research on this topic.

References


An exploratory analysis of internet banking adoption


**Appendix A: survey instruments and items**

**Perceived security**

*PS1*: The personal information that I provide on my bank’s website is secure

*PS2*: My bank’s website is secure and reliable

*PS3*: Using internet banking is financially secure

*PS4*: I would feel secure sending sensitive/personal/financial banking information across the bank’s website

**Perceived ease of use**

*PEOU1*: My interaction with the Internet banking systems (bank’s website) is clear and understandable

*PEOU2*: Interacting with my bank’s website does not require a lot of mental effort

*PEOU3*: I would find the Internet banking systems (bank’s website) easy to use

*PEOU4*: I find it easy to locate the information that I need in my bank’s website
Appendix A: survey instruments and items (continued)

Perceived usefulness

PU1: I think my bank’s Website is valuable to me
PU2: My bank’s Website is functional
PU3: I would find the Internet banking systems (bank’s website) convenient
PU4: Overall, I find my bank’s website useful

IB Adoption

I use online banking for:
- Informational purposes only (e.g., check my account balance)
- Both transactional and informational purposes (e.g., transfer funds between different accounts, pay my bills, pay my credit card statement)
- Not Applicable

Internet experience

How many years have you been using the internet? ____________________________

Computer experience

How many years have you been using computer? ____________________________

Age ____________________________

Status
- Married
- Single
- Other

Gender
- Male
- Female

Education
- 12th grade or less
- Graduated high school or equivalent
- Some college, no degree
- Bachelor’s degree
- Master’s degree or higher
Appendix A: survey instruments and items (continued)

Computer experience

Annual Household Income
- Less than $12,000
- $12,000 to $23,999
- $24,000 to $35,999
- $36,000 to $47,999
- $48,000 to $59,999
- $60,000 to $74,999
- $75,000 to $99,999
- $100,000 or more

Appendix B: Validity and reliability

Table B1  Factor analysis with varimax rotation

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>PEOU1</td>
<td>0.602</td>
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</tr>
<tr>
<td>PEOU2</td>
<td></td>
<td>0.818</td>
<td></td>
</tr>
<tr>
<td>PEOU3</td>
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<td>0.722</td>
<td></td>
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<tr>
<td>PEOU4</td>
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<td>0.781</td>
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<tr>
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<td>PS4</td>
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</table>

Values below 0.45 have been suppressed for clarity (variance explained 80%).

Table B2  Reliability test

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<thead>
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<th>Cronbach’s α</th>
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<tr>
<td>Perceived ease of use</td>
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<tr>
<td>Perceived security</td>
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