CHAPTER 2

THE SOCIO ECONOMIC IMPACT IN ADOPTION OF E-BANKING AMONG SALARIED EMPLOYEES

2.1 Introduction

A famous quote by McLuhan (1957) says "as technology advances, it reverses the characteristics of every situation again and again. The age of automation is going to be the age of do it yourself." As human race evolved over the ages technological advances and the urge to invent newer technologies went hand in hand. Over the last two centuries human race has created innumerable progresses in science, medicine and technology. The evidences of technology adaptation can be seen everywhere, from the large spacecraft to a small hand held smart phone. The dependencies on such technology have become inevitable and are now considered as the fourth necessity for life after air, water and food. The technological revolution, seen the rise of internet and information communication technology and in today's generation, almost every single transaction in the organization is dependent on information communication technology. In the current era of technology revolution, no industry in the world is untouched to the use of information system and banking industry is no exception. According to Gulati, Sivakumaran, and Manogna (2002) bank automation in India dates back to early 1970's with the use of bulky IBM machines involving the laborious process of feeding data on punched cards were confined to complex inter-bank reconciliation and payroll accounting. Most of the public sector banks at that time started to get out of the legacy manual systems and began computerized banking to sustain in the

competition with emerged private sector banks. With the emergence of World Wide Web and networking technologies and also because of low cost of the networking communications, banks in India led to the integration of branches throughout the country. Core banking applications helped a bank to shift from 'branch banking' to 'bank banking.' Competition and the constant changes in technology and lifestyles have changed the face of banking. Nowadays, banks are seeking alternative ways to provide and differentiate amongst their varied services. Customers, both corporate as well as retail, are no longer willing to queue in banks, or wait on the phone, for the most basic of services (Rani and Komal, 2012). Turner, (2001) highlighted that due to growing competition and sophisticated technology led the Indian commercial banks adopt electronic banking.

To the banks the use of electronic banking has several advantages like saves transaction costs, enhance mass customization, marketing and communication activities and to maintain and attract customers. To the customers the advantages can be leveled as easier access to bank accounts and saves time and costs (Kim, Widdows, & Yilmazer, 2005). Although consumers has increased interest in experiencing new technologies put forward by the banking institutes towards the consumers but till now many consumers use the legacy manual systems and tools for banking transactions and hence the new electronic banking tools and techniques have not substituted cent percent the traditional tools. Many researches have taken place to study the adoption of internet banking and electronic banking in this regard, to cite (Tan, Teo, 2000), (Wungwanitchakorn, 2002), (Wan, Luk, & Chow, 2004) , (Akinci, Aksoy, & Atilgan, 2004), (Centeno, 2003) , (Chang Y. T., 2003),

(Khandelwal, 2013) and many others. The following table 2.1 illustrates different influencing factors considered in different studies for adoption of E-banking.

Table 2.1 Factors influencing adoption of Internet Banking and Electronic Banking

Author(S)	Factors Considered
(Wungwanitchakorn, 2002)	Personal characteristics and perceived characteristics
(Akinci, Aksoy, & Atilgan, 2004)	Demographic , attitudinal and behavioral characteristics
(Centeno, 2003)	Access technology and infrastructure, sector specific internet banking, socio economic factors
(Zheng, 2010)	Service quality factors and socio economic factors
(Wan, 2005)	Demographic variables and psychological beliefs
(Chang Y. T., 2003)	Socio economic factors
(Khandelwal, 2013)	Access technology and infrastructure, specific internet banking factors, demographic factors
(Nasri, 2011)	Demographic factors , access technology and infrastructure, specific internet banking factors
(Izogo, Nnaemeka, Onuoha, & Ezema, 2012)	Demographic factors
(Mavetera & Kesimolotse, 2007)	Socio economic factors
(Mattila, Karjaluoto, & Pento, 2003)	Socio economic factors
(Lichtenstein & Williamson, 2006)	Consumers' attitude, bank infrastructure and ability to attract.
(Laukkanen & Pasanen, 2008)	Socio economic factors

From the available literature it is well understood that demographic and socio economic factors are the major influencers of adoption of electronic banking. Thus, the current chapter involves the study of socio economic factors and its impact on electronic banking adoption among salaried employees.

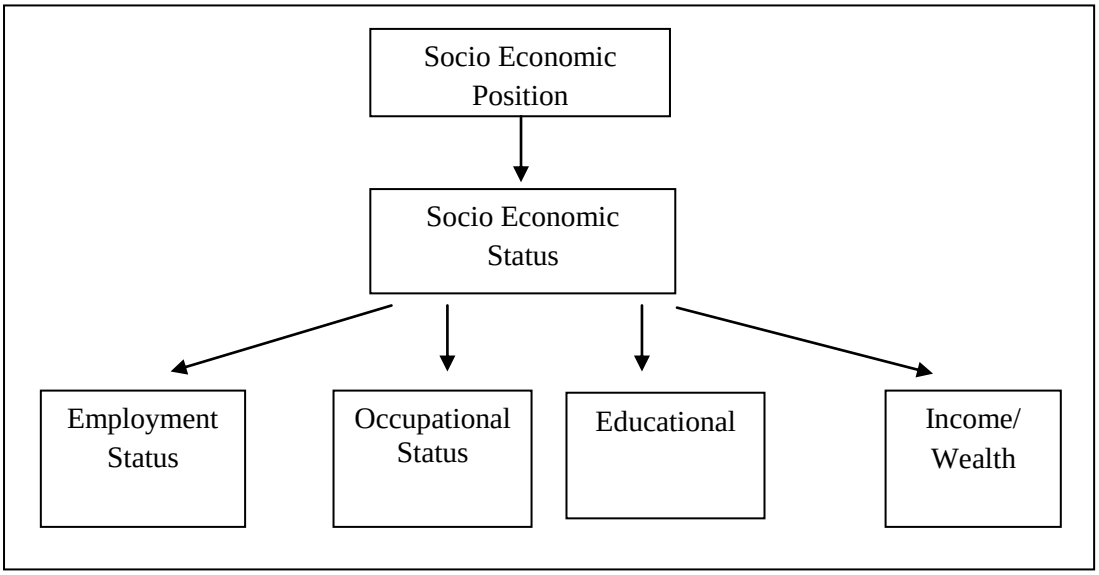
2.2 Socio Economic Status

Socio economic status is generally measured by different variables in different studies which makes it difficult to appreciate exactly what it is, or what researchers or policy makers mean by socio economic status (National Centre for Education Statistics, 2012) (Australian Government, Department of education, employment and workplace relations, 2009). Again (Australian Government, Department of education, employment and workplace relations, 2009) defined socio economic status broadly in terms of social, cultural and economic resources, the extent to which individuals and groups' have access to these resources and the relative value ascribed to the resources held by different individuals and groups. Socio economic status refers to a finely graded hierarchy of social positions which can be used to describe a person's overall social position or standing. It can be indicated by a number of (sub-) concepts such as employment status, occupational status, educational attainment and income and wealth (Graetz, 1995).

Similarly Hirsch, Kett, and Trefil (2002), defined socio economic status as an individual's or group's position within a hierarchical social structure. Socio economic status depends on a combination of variables, including occupation, education, income, wealth, and place of residence. Sociologists often use socioeconomic status as a means of predicting behaviour.

According to Aue and Roosen (2010), socio economic status can be divided into material factors and psychological factors. Material factors include financial aspects, especially the income situations which influence psychological aspects like stress, subsequent risk taking behaviour. A socio economic gradient depicts the relationship between a social outcome and socio economic status for individuals in a specific community. The social outcome can be any measurable trait (Willms, 2002) and social class is measured by indicators such as income, occupation and education (Haynes, 2011). Akinbile (2007) says that, the concept socio economic status could be defined as the position that an individual or family occupied with respect to the prevailing average standards of cultural possessions, effective income, material possessions as well as participation in the group activities of the communities. According to Marks, McMillan, Jones, and Ainley (2000), socio economic status is usually understood as multidimensional concept.

Figure 2.1: Concepts relating to socio economic position.



Source: (Marks, McMillan, Jones, & Ainley, 2000)

2.2.1 Socio Economic and Demographic factors identified

Socio-economic status (SES) is a combined measurement of economic and social position of an individual or a group in relation to others in the society (Roy, Chandra, Kharbikar, Joshi, & Jethi, 2013). It also guides the psychological and behavioral components of a sample viz. knowledge, attitude, perception, risk bearing ability and adoption (Roy, Chandra, Kharbikar, Joshi, & Jethi, 2013). The socio economic and demographic factors identified are as follows.

2.2.1.1 Age, Gender and Marital status

The study of (Akinci, Aksoy, & Atilgan, 2004) highlights that there is a significant difference between age groups with respect to internet banking use. According to Akinci, Aksoy, and Atilgan (2004) majority of the customers are male. Polatoglu and Ekin (2001), in his study found that internet banking users are young and affluent. Similarly Barnett (1998) says that younger customers are more comfortable with using internet banking compared to older customers. Again a Finnish study shows that Internet banking users is middle aged (Mattila & Pento, 2002). AL-Ashban and Burney (2001) found that in Saudi Arabia adoption of tele banking is negetively associated with age. Chang (2003) , in his study 'Dynamics of Internet Banking Adoption', found that 45 years old or more is more likely to adopt internet banking than younger generations between ages 13-24, Females are marginally more likely to adopt internet banking than males and at the same time marital status also influences internet banking adoption. Khandelwal (2013), Laukkanen and Pasanen (2008), Suoranta and Mattila (2004), Nasri (2011), said that demographics play an important role in the adoption of E banking facilities as we

have seen that age and gender factor considerably affects the adoption. Izogo, Nnaemeka, Onuoha, and Ezema (2012) found that age and marital status significantly effects E-banking adoption. Margaret and Ngoma (2013) found in his study that age and gender have positive relationship with internet banking adoption. The study of (Fonchamnyo, 2013) finds that age and marital status has significant influence on E-banking adoption. Similarly Izogo, Naemeka, Onuoha, and Ezema (2012) also investigated and found that influence of age and marital status on E-banking adoption is significant.

2.2.1.2 Education

Mattila, Karjaluoto, and Pento (2003) suggest that education has a significant impact on internet banking adoption. As the education level increases, people who have attended the courses should have more knowledge and skills and therefore perceived Internet banking as more user-friendly (Nasri, 2011). Polatoglu and Ekin (2001) also said that internet banking users are highly educated which is consistent with (Al-Ashban & Burney, 2001), (Stavins, 2001) (Izogo, Naemeka, Onuoha, & Ezema, 2012). Wan, Luk, and Chow (2004) in their study of adoption of banking channels in Hong-Kong found that education level was significantly associated with the adoption of branch banking and internet banking but not with other channels. A lower education level was associated with heavier reliance on branch banking whereas internet banking by customers with moderate education level. Again (Chang Y. , 2003) had some opposite results, according to his findings people with higher education are less likely to adopt internet banking because of

cautious behavior. Similarly Laukkanen and Pasanen (2008) says that education does not have any impact in adoption of mobile banking.

2.2.1.3 Household Income

Centeno (2003)**,** suggest that family income is one of the socio economic factors that can influence internet banking adoption. Chang (1997) establishes that income is the single most important variable that influences a consumer's use of a credit card. A number of studies relate that income has a positive relationship with adoption of E-banking (Hein & Bauer, 2006), (PriceWaterhouseCoopers, 2000), (Goldsmith & Flynn, 1993), (Sakkthivel, 2006), (Al-Ashban & Burney, 2001), (Stavins, 2001), (Karjaluoto, 2002), (Zheng,2010), (Mattila, Karjaluoto, & Pento, 2003). Difference of opinion obtained from (Izogo, Naemeka, Onuoha, & Ezema, 2012) that income and E-banking adoption are statistically insignificant.

2.2.1.4 Family size and earners in the family

Heikki, Minna, and Tapio (2002), explored the effect of different factors affecting attitude formation towards internet banking in Finland. Their results reveal that online banking usage correlates positively with household size. Some other studies like (Mattila, Karjaluoto, & Pento, 2003), (Ding, Verma, & Iqbal, 2007), (Howcroft, Hamilton, & Hewer, 2002) mentioned that the family size effects internet banking adoption. Again the study of (Laukkanen & Pasanen, 2008) found that size of household do not influence mobile banking adoption.

2.2.1.5 Job level

In this study we are concerned about finding out the E-banking adoption among salaried employees irrespective of government, public and private organization etc. But different organizations have different classification of employees and different job grades and levels. Hence a common representation for job level needs to be identified for suitability in all types of organization. According to (Bureau of Labor Statistics, 1980) adopted in the study of (Schwenk, 1997), the different job levels can be represented in the three ways: blue collared workers, white collared workers and service. Some other definitions of white collared workers can be cited from (Prandy, Stewart, & Blackburn, 1982) book on white collar work. They used the term ‘‘white collar’’ to refer to non-manual labor, e.g., supervisors, clerks, professionals, and senior managers. Coates (1986) divided white-collar work into three categories: clerical, professional, and managerial. Again according to Schwerdt, Ichino, Ruf, Winter-Ebmer, and ZweimÄuller (2009) white and blue collar workers are defined according to administrative rules: white collar workers comprise all clerical workers and higher non-clerical (manual) occupations, including salespersons (excluding waiters and salespersons in bakeries, etc.); blue collar workers are typically manual workers.

Table 2.2 Examples of occupations found in major occupational groups within the scope of ECI

Type of Worker	Occupation category	Examples of Occupation
White Collared Workers	Professional specialty	Engineers, mathematicians, chemists, physicians, registered nurses
	Technicians and related support technicians, airplane pilots	Dental hygienists, licensed practical nurses, mechanical engineering
	Executive, administrative, and managerial	Financial and other managers, accountants and auditors
	Sales	Insurance sales, cashiers
	Administrative support including clerical mail clerks, insurance adjusters	Computer equipment operators, secretaries, hotel clerks, bookkeepers
Blue Collared Workers	Precision production, craft, and repair butchers, power plant operators	Air conditioning mechanics, carpenters, electricians, tool and die makers
	Machine operators, assemblers, and inspectors	Metalworking machine operators, assemblers, production inspectors
	Transportation and material moving	Truck drivers, railroad conductors, operating engineers
	Handlers, equipment cleaners, helpers	Construction laborers, freight, stock, and material handlers and laborers
Service Workers		Guards, waiters and waitresses, nursing aides, janitors, barbers

Source: Bureau of Labor Statistics, 1980 (Schwenk, 1997)

As far as adoption of electronic banking is concerned, the study of (Bryan & Wang, 2013) says that part time workers perceive electronic banking as costly and prefer not to adopt it, whereas white collared workers exhibit a positive attitude towards adoption of E-banking services compared to blue collared workers. Karjaluoto, Mattila, and Pento (2002) in their study found that occupation was a significant factor for adoption of Internet banking. They divided occupation into two groups, white-collar workers and blue-collar workers. White-collar workers were more likely to adopt internet banking than blue-collar workers.

2.2.1.6 Location (Area of residence)

The location or area of residence of the respondents can be either rural or urban. Some studies found the impact of area of residence in adoption of electronic banking. The study of (Onyia & Stephen, 2011) found that area of residence to be correlated with adoption of internet banking. Similarly other studies also found evidence of relationship between places of residence and customer intention to use internet banking (Laforet & Li, 2005), (Lichtenstein & Williamson, 2006) and (Premalatha & Sundaram, 2014). Again the study of (Khan & Emmambokus, 2011) comments that area of residence is insignificant in adoption of internet banking in developing countries.

2.2.1.7 Banking Characteristics (Frequency of use of banking services)

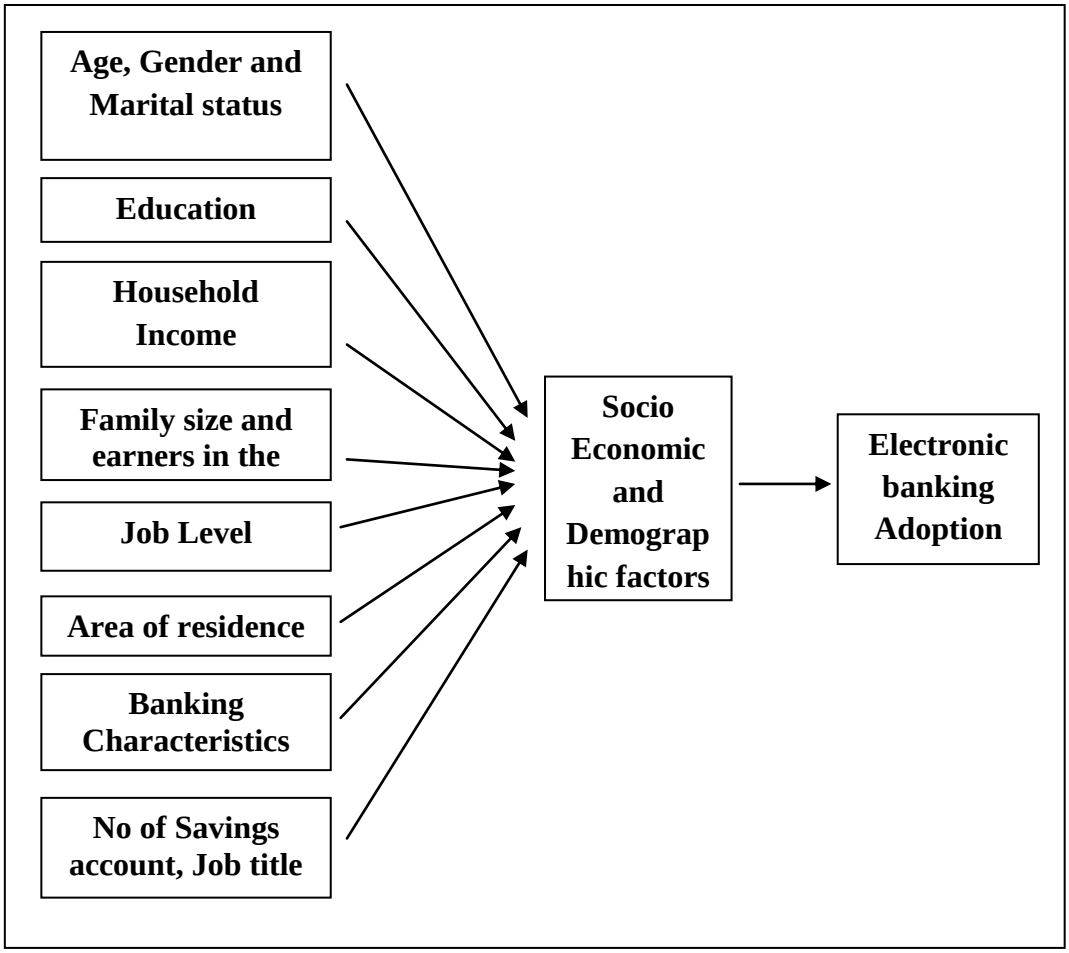
Frequency of use of banking services or the banking habit of customers can be a factor for adoption of electronic banking. Since the literature study reveals that the advantage of E-banking use is easier access to bank accounts and saves time and

costs (Kim, Widdows, & Yilmazer, 2005), thus those customers whose frequency of use of banking services is more, i.e. they avail common banking transactions like withdrawal of money, deposit of money, fund transfer, balance enquiry etc. from their respective banks frequently, probability is there that they can go for time saving and cost saving and thereby adopt E-banking services. The study of (Gunasekaran & Rajagopalan, 2013) also cites the same. According to the study the adoption of E-banking is significantly associated with the number of banking transactions per month among bank customers. Similarly Sivaramakrishnan and Swaaminathan (2014) wanted to find the relationship between numbers of times visiting bank in a month and adoption of online banking facilities and found it to be significant.

2.2.1.8 Number of savings account, Job title

In this study two other socio economic factors are taken into consideration such as, first, the number of savings account salaried people have and second, the job title i.e. whether the salaried employee is from private sector, public sector, government sector or an autonomous body. These two factors shall also be examined to find out the impact if any in adoption of electronic banking among salaried employees.

Figure: 2.2 Socio Economic factors in Adoption of Electronic Banking



Source: Author

2.3 Methodology

This section deals with the methodology adopted in this chapter.

2.3.1 Logic behind E-Banking adoption

Individual past experience and behaviour, trust, price sensitivity, tastes, income and future expectations are assumed to be some of the factors that influence consumption behaviour. Beckerian economic approach to human behaviour

emphasised time as a major factor in maximising utility in consumption. Becker (1971) revised the consumption model using commodities and time to produce a specific good. Again in the equity-based model which states the even exchange of values such that what is received is presumed to be equal to what is given **(**Adams**,** 1965**)**, motivational forces in such equity based models include sensitivity of consumers toward primarily price, time and effort expended (Gabor & Granjer, 1966). These models made it possible to explain the relationship between opportunity cost of time for labour participation and consumption, through combining time value and price of commodities within budget constraints (Kim, Widdows, & Yilmazer, 2005). As time was considered in the consumption model, effects of time saving products could be investigated within the model. (Ekelund & Watson, 1994) indicated that time-saving technologies or goods for households all can be explained within the Beckerian nexus.

E-banking and its delivery channels has the capacity to save time and costs. And thus the attitude of consumers will be different since their response to E-banking will be different as they have different opportunity cost of time for labour, ability and other factors.

2.3.2 E-banking Adoption Model

To understand the adoption attitude of the consumer an adoption function is formulated which is used in (Kim, Widdows, & Yilmazer, 2005) and it follows (Trajtenberg,1989) and (Trajtenberg, 1990) approach which assumed that a consumer will accept a new product if the difference between the utility of the new

product (U_{new}) and the utility of existing one (U_{old}) exceed some threshold value ($\delta>0$),

$$(\mathbf{U_{new} - U_{old}}) > \boldsymbol{\delta},$$

where U_{new} is the utility function for different goods and services including a new commodity, electronic banking, for money transactions.

The consumers maximize their utility within a subset for money transactions,

$$U_i = f(X_i, t_i; R),$$

X_i is a vector of input for different goods for technology i, t_i is a vector of inputs of time for technology i, and R is a proxy variable for tastes for new and old technologies. We create a new adoption function by substituting the utility function above;

$$[f(X_{new}, t_{new}; R) + \epsilon_{new}] - [f(X_{old}, t_{old}; R) + \epsilon_{old}] > \delta,$$

where i = new , denotes the new technology, and i= old, denotes the old technology, ϵ_i is the effect of unobserved factors. The above equation can be rewritten as follows:

$$-n < U^*,$$

Where $U^* = f(X_{new}, t_{new}; R) - f(X_{old}, t_{old}; R) - \delta$ and $n = \epsilon_{new} - \epsilon_{old}$

From the function above, this study investigates which consumers (who have different tastes) are more likely to adopt electronic banking, so the dependent variable has a binary code, whether consumers adopt enternet banking or not. The model has a probability function as follows:

$$Y= f(Z, \beta) + \varepsilon, Y= 0, 1$$

Pr *(Electronic banking is adopted, or Y=1)* = Pr $(-\eta < U^*)$

Pr *(Electronic banking is not adopted, or Y=0)* = 1- Pr $(-\eta < U^*)$,

where Z includes socio economic aspects like gender, age, education, income, financial assets, marital status, family size, number of earners in the family, job level etc .

Through the function above, it is possible to determine which factors will significantly affect consumers' adoption behaviour for electronic banking. Also, this investigation will capture individuals' specific threshold value for the adoption of electronic banking.

2.3.3 Tools to be used

In this study we find that dependent variable is the adoption of electronic banking channels which is to be predicted from different independent variables like gender, age, education, income, occupation, financial assets, marital status, family size, number of earners in the family, level of employee etc. Multiple regression is a flexible method of data analysis that may be appropriate whenever a quantitative

variable (the dependent or criterion variable) is to be examined in relationship to any other factors (expressed as independent or predictor variables) (Berger, 2003).

A multiple regression equation for predicting Y can be expressed a follows:

$$Y' = A + B_1X_1 + B_2X_{12} + B_3X_3 \ldots\ldots\ldots\ldots + B_nX_n + \varepsilon \quad \ldots\ldots (1)$$

The dependent variable i.e. the adoption of electronic banking will have two responses. Either a person can adopt the E-banking channels alternatively he or she doesn't adopt E-banking delivery channels. The adoption of electronic banking channels may be represented as '1' and not availing or adopting E-banking channels may be represented as '0'. Hence we find that this is the case of regression model where the dependent variable or response variable is dichotomous in nature, taking either Yes (1) or No (0) value.

The most commonly used approaches to estimate such models are the

i) Linear Probability model,

ii) The Logit model and

iii) The Probit model.

But there are certain problems associated with the estimation of linear probability models such as non-normality of the disturbances, heteroscedestic variances of the disturbances, non fulfilment of $0 \leq E(y/x) \leq 1$, questionable value of R^2 as a measure of goodness of fit. (Vasisht, 1999).

When (i) *y* is continuous, y can take values between plus and minus infinity and in practice y assumes finite values from $-k \leq y \leq +k$, which poses no problem.

(ii) But when y is binary, some of the OLS Model or the linear probability models are not valid and the resultant model will exclude potentially important variable and provide unreliable estimates. This is because error term do not have equal variances and error terms are not normally distributed (Ratner, 2009).

As we considered in no (ii) above that y is binary, which is the observed binary variable. Let us assume that there is an unobserved latent variable y* ranging from -∞ to +∞ that generates the observed y. Those who have larger values of *y** are observed as *y* = 1, while those with smaller values of *y** are observed as *y* = 0 (Long, 1997). One person might be very close to adopting E banking channels while another person could be very firm in using E-banking delivery channel. In both cases, we observe the same *y* = l .The idea of a latent *y** is that there is an underlying propensity to choose the E-banking channels that generates the observed state.

The latent y* is assumed to be linearly related to the observed x's through the structural model:

$$y_i^* = X_j \beta + \varepsilon$$

The latent y* is linked to the observed binary variable y by the measurement equation:

$$y_i = \begin{cases} \mathbf{1 \ \ if \ y_{i*} > r} \\ \mathbf{0 \ \ if \ y_{i*} \leq r} \end{cases}$$ Where r is the threshold or cut point

Now since y* is continuous, the model avoids the problems encountered in linear probability model. However, since the dependent variable is unobserved, the model

cannot be estimated with ordinary least square instead maximum likelihood estimation which requires assumption about distribution of errors can be used. The choice is between normal errors which result in probit model and logistic errors which result in logit model. Thus the data gathered will be analysed by either probit regression analysis or logistic regression analysis based on (Kim, Widdows, & Yilmazer, 2005), (Laukkanen & Pasanen, 2008). Since the choice of probit versus logit depends largely on individual preferences (Patnaik & Sharma, 2013).

Here in this chapter the logit model is used to find the factors responsible for adoption of electronic banking among salaried employees which follows (Wungwanitchakorn, 2002).

Logistic Regression equation is given by:

$$\mathbf{Log\,(p/1-p) = B_0 + B_1x_1 + B_2x_2 + B_3\,x_3 \ldots\ldots\ldots\ldots + B_nx_n} \quad \ldots\ldots\ldots\ldots (2)$$

Where B values are the estimates in log odds units, p is the probability of E-banking adoption.

2.4 Hypothesis of the study

The current hypothesis of the study is socio-economic factors have an impact in adopting E-banking delivery channels among salaried employees. Thus we are to find out that socio economic factors like age, gender, marital status, education, house hold income, job title, job level, number of savings account, number of earners in the family, number of family members, banking characteristics and area of residence has any impact on adoption of E-banking among salaried employees.

2.5 The Data

The data collected for the study follows the methodology described in chapter one. A survey was conducted keeping in mind the study area i.e. Cachar, Hailakandi and Karimganj districts of Assam and the list of banks mentioned in chapter one. A total of 400 respondents were collected adopting post stratified random sampling. The number of respondents collected from each bank was based on proportional allocation that they contribute in the total population. Since the study is related to the adoption of E-banking and hence equal numbers of respondents were collected for E-banking adopters and non adopters. The respondents whether they use electronic banking was characterized by the use of Internet banking or mobile banking or ATM or credit card banking channels. Any respondents who use any one of the mentioned banking channels were characterized to be E-banking users and adopters. All other respondents who use none of the above mentioned channels were characterized and grouped under E-banking non users and non adopters. The age profile of the respondents in years were collected and are grouped under 5 categories, "below or equal to 20", "21-30", "31-40", "41-50" and "51 and above". The gender of the respondents were also collected and incorporated in the study. The location or the areas of residence were collected based on whether a respondent is residing in rural area or in urban area which are obtained from the address mentioned by the respondents. Similarly, education level of the respondents were grouped into "Below Matriculation", "Matriculation", "Higher Secondary", "Graduate", "Post-Graduate", and "Others". Marital statuses were grouped into "Married", "Single", "Separated", and "Widowed/Widower". Job

levels of the salaried employee respondents were grouped among "White Collared Employee", "Blue Collared Employee" and "Service Employees". The type of Job or Job title was grouped between "Private Sector", "Public Sector", "Government Employee" and "Autonomous Body". The number of savings account a respondent is availing; total number of family members and number of earners in the family were also collected. The house hold income was grouped in to " up to Rs 200000", " Rs 200001- Rs 500000", "Rs 500001-Rs 700000", "Rs 700001-Rs 1000000" and "Rs 1000001 and above". Finally the frequencies of banking transactions and frequencies of E-banking transactions were also collected based on categories such as "Daily", "Few Days a week", "Once in a week", "Few days a month", "Once in a month" and "Rarely". Those who did not use E-banking need not mention the frequency of E-banking use. The frequencies of the variables and the variable categories are mentioned in appendix Table A1.

2.6 Descriptive Statistics

The descriptive statistics of the data are presented in the Table: A1 in the appendix. As stated above, 50 percent of the respondents are E-banking adopters and rest 50 percent are E-banking non adopters. If we consider internet banking then, 95 respondents out of 400 use internet banking i.e. equivalent to 23.8 percent, whereas 76.3 percent does not avail internet banking. The usage of mobile banking can be appreciated to only 13 percent of the respondents and rest 87 percent are non users of mobile banking. Poorer is the condition with the usage of credit card. Only 10 percent of the respondents use credit card as one of the means of E-banking and rest 90 percent are non users of credit card. But the reverse is with the usage of

ATM. As regards to ATM, almost 49.8 percent of the respondents use ATM and 50.2 percent does not do so. Again if only E-banking users are considered then, it can be interpreted that amongst those who use E-banking, almost 99.6 percent of them use ATM. The gender wise distribution is such that the sample comprises of 359 males against 41 females with percentages 89.8 percent and 10.2 percent respectively. Age-wise distribution shows that we have maximum of the respondents belonging to the age group 51 and above with 39.8 percent, followed by age group 41-50 with 25.8 percent, 31-40 with 16 percent, 21-30 with 17.8 percent and below or equal to 20 with 0.8 percent. There is not much difference in proportions as far as the area of residence and location is concerned. Almost 58 percent of the respondents belong to urban area and 42 percent belong to rural area.

From the Table: A1 in the appendix , the educational back ground of the respondents is found to have mixed responses with highest responses came in the group matriculation 28.3 percent flowed by graduate with 27.8 percent and least percentage of 1 percent attributed to group others. The marital status showed that highest responses belong to married group with 75.5 percent followed by single with 20.3 percent and least with separated with1.3 percent. The white collared workers seemed to be the majority groups with 49 percent as far as the level of job is concerned followed by blue collared with 36 percent and service by 15 percent .Most of the respondents were found to belong to government employees with 68.3 percent followed by private sector 15.5 percent and public sector with 48.5 percent. The reason may be attributed to less private jobs availability in the study area. As far as the number of savings account is concerned majority of the respondents 59.8

percent mentioned that they have only one single savings account followed by 27.8 percent with two savings accounts. Income wise distribution of the respondents showed that majority of the respondents 47.8 percent mentioned that their household income is in the group Rs 200001-Rs 500000, followed by 29 percent for up to Rs 200000. Majority of the respondents seemed to belong to families with 4 persons being the maximum with 41 percent, followed by 5 persons with 25.8 percent and 3 persons with 21 percent. The result reversed for the number of earners in the family. 68.5 percent of the respondents mentioned that they are the sole earners followed by 24.8 percent with two earners in the family. The banking characteristics of the respondents seemed to be diverse with once in a month banking transactions being the maximum with 32 percent followed by 29.5 percent few days a month followed by once a week and few days a week with 14 percent and 12.8 percent respectively. Similarly those who use E-banking facility, among them majority do the transactions electronically few days a month with 31.5 percent, followed by once a week and few days a week with 24.5 percent and 23.5 percent respectively. Thus here we find a difference of opinion among users and non users of E-Banking. Those who use E-banking, majority do transactions electronically few days a month, but those who do not use E-banking, majority of them do transactions once a month.

2.7 Analysis and Results

For the main analysis the data was entered into IBM SPSS 19. The independent variables such as number of savings account, number of earners in the family, number of family members are ordinal variables which are not categorical.

Whereas the variables like gender, location of residence, age, educational level, frequency of banking use, marital status, job level, job title, gross household income are considered as categorical in the study. Again out of all these categorical variables gender, location are binary categorical variables whereas age, educational level, frequency of banking use, marital status, job level, job title, gross household income are categorical of more than two levels and hence for these type of variables, dummy variables are needed to be created for making it binary categorical variable (Wuensch, 2014). Again the number of dummy variable to be created for a single variable is (k-1), where k is the number of categories of that variable (Wuensch, 2014). Keeping view of the fact that (k-1) dummy variables need to be created, hence we create the dummy variables for the most important categories in the variable and the least important variable is sacrificed from the analysis. Thus we have age (4 dummy variables), educational level (5 dummy variables), frequency of banking use (5 dummy variable), marital status (3 dummy variable) etc. The dummy variables along with other predictor variables can be seen in Table A2 in appendix. At first the binomial logistic regression was done for overall E-banking and later for individual E-banking channels.

2.7.1 Results of E-banking users

For dependent variable electronic banking use (Yes/No), the conduct of the Binary Logistic regression provided the following results:

Model Fitting:

At first different test associated with model fitting were checked followed by actual results.

Table: 2.3.1 Omnibus Tests of Model Coefficients for E-Banking users (Equation 2)

		Chi-square	Df	Sig.
Step 1	Step	506.786	31	0
	Block	506.786	31	0
	Model	506.786	31	0

The omnibus test of model Coefficients presented in table 2.3.1, reports the chi-square associated with each step in a stepwise model. Here it has only one step from constant model to the block model so all the three p values are same. The significant value or p-value indicates whether the model (Block 1; with predictors) is significantly different from the constant only model (Starkweather, 2014). Here in our model the p value is significant (.000 < .05) and hence we can conclude that there is a significant effect for the combined predictors on the outcome variable. Thus, the null hypothesis is accepted that there is a significant effect of socio economic factors taken together in adoption of E-banking among salaried employees.

Table 2.3.2 Model Summary for E-Banking users (Equation 2)

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	47.732[a]	0.718	0.958

The model summary presented in the table 2.3.2 represents the -2 Log Likelihood which represents the unexplained variance in the outcome variable, therefore the smaller the value the better the fit (Starkweather, 2014). Here in this model we have the value of-2 Log Likelihood is 47.732[a], which is smaller in value. The Nagelkerke estimate presented in Table 2.3.2 is calculated in such a way as to be constrained between 0 and 1. So, it can be evaluated as indicating model fit; with a better model displaying a value closer to 1. Here in this model, Nagelkerke R square value obtained is 0.958 which is very close to one, indicating a very good fit.

Table 2.3.3 Hosmer and Lemeshow Test for E-Banking users (Equation 2)

Step	Chi-square	Df	Sig.
1	0.853	8	0.999

The Hosmer and Lemmeshow test presented in the table 2.3.3 is the preferred test of Goodness of fit. Here p value needs to be greater than established cut off (generally 0.05) to indicate a good fit (Starkweather, 2014). Here the p value obtained is 0.999 > 0.05 with chi square 0.853, indicating a good fit.

Now logistic regressions are interpreted on the basis of B value or Odds ratio [EXP(B)] and significance (p value). B value or the log odds (see equation 2 mentioned earlier) are the estimates in log odds units which tell about the relationship between the independent variables and the dependent variable, where the dependent variable is on the logit scale[1]. These estimates tell the amount of increase or decrease, in the predicted log odds of dependent variable. The log odds are the logarithm of the odds ratio which is an alternative way of expressing probabilities[2].

EXP(B) are the odds ratios. Odds are determined from probabilities and range between 0 and infinity. Odds are defined as the ratio of the probability of success and the probability of failure[3]. Although probability and odds both measure how likely it is that something will occur[4]. Thus both log odds and odds ratio is an alternative measure of probability.

When B value is positive then slope is positive i.e. positive relationship and Odds ratio or EXP(B) is greater than 1. When B value is negative then slope is negative i.e. negative relationship and Odds ratio EXP(B) is less than 1. When B value is zero, EXP (B) is 1 with no linear relationship[5].

The odds ratio can be expressed as percentage [6] by the formula[7], [EXP (B)-1] × 100 percent[5].

[1] http://www.ats.ucla.edu/stat/spss/output/logistic.htm
[2] https://wiki.lesswrong.com/wiki/Log_odds
[3] http://www.ats.ucla.edu/stat/stata/faq/oratio.htm
[4] http://www.theanalysisfactor.com/why-use-odds-ratios/
[5] *global.oup.com/us/companion.websites/fdscontent/uscompanion/us/.../Chapter2.ppt*
[6] *https://analytics.kennesaw.edu/~jpriestl/STAT4490/LOGISTICpercent20NOTES.ppt*

The results of the logistic regression for E-banking described in the Table A2 in the appendix, helps to find that the factors such as gender, number of savings account, number of members in the family, age, job level, job title and income does not contribute to the model and are statistically insignificant after conducting the Wald test, whereas the factors such as location of residence, earners in the family, educational level, frequency of banking transaction and marital status are significantly contributing to adoption.

Now, the effect of the significant factors on the adoption of E-banking channels, are explained individually.

For the variable 'location of residence of the respondents', the values from Appendix table A2 can be interpreted as follows, the respondents from urban area are 6 times (Odds Ratio 6.11) more likely to adopt E-banking channels compared to a rural customer. Thus, from this we can find that if a person is from urban area, the chance of E-banking adoption is very high compared to rural area.

For the variable 'number of earners in the family' the values (Appendix table A2) can be interpreted as with increase in one unit of earner in the family, increases the chance of E-banking adoption by 1.74 times (Odds Ratio 1.74). Thus here we find that as number of earners in the family increases, the chance of E- banking adoption also increases.

As far as educational level is concerned only three categories of education out of five are significant on adoption of E-banking (see Appendix table A2). Thus, from

[7] *faculty.arts.ubc.ca/tindall/soci508/slides/LogisticRegression[1].ppt*

the values we find that a respondent who is having 'Higher Secondary educational level' are almost 4 times (odds ratio is 3.815) more likely to adopt E-banking compared to the respondents who are below matriculation (reference category). Similarly a respondent with 'Graduation level of education' are almost 7 times (odds ratio is 6.82) more likely to adopt E-banking compared to respondents who are below matriculation. Likewise a respondent with 'Post Graduate level of Education' are 3.74 times (Odds Ratio 3.74) more likely to adopt E-banking compared to the respondents who are below matriculation. Thus we can say that more the education level, the more is the chance of E-banking adoption.

For the 'frequency of use of banking services', the categories such as transactions 'once a week' and 'few days a month' (significant at 10 percent level) are significant for adoption of E-banking (see appendix table A2). From the values it is found that, a respondent who does banking transactions at least once a week , are 3.76 times (odds ratio 3.76) more likely to adopt E-banking compared to the respondents who does banking transactions rarely (reference category). Similarly those respondents who do banking transactions at least few days a month, they are 3.22 times (odds ratio 3.22) more likely to adopt E-Banking compared to those who does banking transactions rarely. Hence those people who does Banking transaction at-least once a week or at-least few days a month are in a better position to adopt E-banking compared to other groups of people with different frequencies of transactions.

The last variable that might have some impact on the adoption of E-Banking is the marital status. From the table A2 in appendix, it is found that single or unmarried

respondents are significant at 10 percent level. The results can be interpreted as a respondent who is single are 5.25 times (odds ratio 5.355) more likely to adopt E-banking compared to the reference category i.e. widow/widower. From this we can say that unmarried single respondents are more probable adopters of E-banking compared to other categories.

Next part of the chapter will deal with results of individual E-banking channels.

2.7.2. Results of Internet banking users

For dependent variable internet banking use (Yes/No), the conduct of the binary logistic regression provided the following results:

Model Fitting:

At first different test associated with model fitting were checked followed by actual results.

Table 2.4.1 Omnibus Tests of Model Coefficients for Internet Banking users

		Chi-square	Df	Sig.
Step 1	Step	292.126	31	.000
	Block	292.126	31	.000
	Model	292.126	31	.000

Here in the model presented in Table 2.4.1, the p value is significant (.000 < .05) and hence we can conclude that there is a significant effect for the combined predictors on the outcome variable.

Table 2.4.2 Model Summary for Internet banking users

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	146.418[a]	.518	.778

From Table 2.4.2 the -2 Log Likelihood is 146.418[a] , which is smaller in value indicating better fit and similarly the Nagelkerke R Square value is close to 1 i.e.0.778 also indicating good fit.

Table 2.4.3 Hosmer and Lemeshow Test for Internet Banking

Step	Chi-square	Df	Sig.
1	9.184	8	.327

The Hosmer and lemeshow test of goodness of fit also indicating a good fit with value 0.327>0.05 with chi square value 9.184.

From the results of the logistic regression described in the Table A3 in the appendix, it can be found that the factors such as number of members in the family and frequency of banking service are found to impact the adoption of Internet banking after conducting Wald test.

For the variable ‘number of members in the family’ (see Table A3 in appendix), it can be interpreted that with increase in numbers of members in the family the adoption of internet banking is 0.387 times (odds ratio 0.387) less likely. This means that with the increase in number of family members the chance of internet banking adoption decreases.

For the variable 'frequency of use of banking service ', categories such as banking transactions 'daily', 'few days a week' and 'once a week', are statistically significant (See Appendix table A3). From the table we can interpret that if a respondent who does banking transactions daily are 4.34 times (odds ratio 4.34) more likely to adopt internet banking compared to those who do banking transactions 'rarely' (reference category). Similarly, a respondent who does banking transactions few days a week are 5.6 times (odds ratio 5.618) more likely to adopt internet banking compared to the reference category. Likewise, those who do transactions once a week, are also 5 times (odds ratio 5.063) more likely to adopt internet banking compared to the reference category. Thus this means that those respondents who does transactions daily, few days a week or at least once a week, their chance of internet banking adoption is more compared to those who does transactions few days a month, once a month and rarely.

All other factors being in-significant do not contribute to the use of internet banking among salaried employees.

2.7.3. Results of Mobile banking users

For dependent variable Mobile Banking use (Yes/No), the conduct of the Binary Logistic regression provided the following results:

Model Fitting:

At first different test associated with model fitting were checked followed by actual results.

Table 2.5.1 Omnibus Tests of Model Coefficients for Mobile Banking users

		Chi-square	Df	Sig.
Step 1	Step	124.309	31	.000
	Block	124.309	31	.000
	Model	124.309	31	.000

Here in the model presented in Table 2.5.1, the p value is significant (.000 < .05) and hence we can conclude that there is a significant effect for the combined predictors on the outcome variable.

Table 2.5.2 Model Summary for Mobile Banking users

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	184.800[a]	.267	.496

From Table 2.5.2 the -2 Log Likelihood is 184.800[a] , which is smaller in value indicating better fit and similarly the Nagelkerke R Square value is .496 indicating moderate fit.

Table 2.5.3 Hosmer and Lemeshow Test for Mobile Banking users

Step	Chi-square	Df	Sig.
1	7.286	8	.506

The Hosmer and lemeshow test of goodness of fit also indicating a good fit with value .506 >0.05 with chi square value 7.286.

From the results of the logistic regression described in the Table A4 in the appendix, it can be found that the factors such as location (significant at 10 percent level), no of earners in the family (significant at 10 percent level), frequency of use

of banking service, marital status are found to significantly impacting the adoption of mobile banking after conducting Wald test.

From the results of variable location obtained from Table A4 in appendix, we can interpret that a respondent from urban area are almost 3 times (odds ratio 2.860) more likely to adopt mobile banking compared to those who reside in rural area. Thus the chance of mobile banking increases with respondent residing in urban area.

For the variable earners in the family from the values (Appendix table 4), it can be interpreted that with increase in earners in the family a respondent is 1.6 times (odds ratio 1.666) more likely to adopt mobile banking. Thus as number of earners in the family increases, the chance of mobile banking adoption also increases.

As far as frequency of use of banking services are concerned categories such as, doing banking transactions daily, few days a month (significant at 10 percent level) and once a month are significantly contributing towards mobile banking adoption. From the results in table A4 in appendix it can be interpreted that, respondents doing banking transactions daily are almost 3 times (odds ratio 2.936) more likely to adopt mobile banking compared to those doing banking transactions rarely (reference category). Similarly, for a respondent who do banking transactions few days a month are 4.4 times (odds ratio 4.395) more likely to adopt mobile banking compared to the reference category. Likewise those who do transactions once in a month are 5.6 times (odds ratio 5.568) more likely to adopt mobile banking compared to the reference category. Hence it can be said that respondents who do

banking transactions daily, few days a month and once in a month are in a better position compared to other categories for adoption of mobile banking.

For the variable marital status, the values from the table A4 in appendix suggests that, respondents who are single are 16 times more likely to adopt mobile banking compared to respondents who are widowed or widower. Similarly, respondents who are married are 12 times more likely to adopt mobile banking compared to the reference category i.e. widowed or widower. Thus it can be said that respondents who are single and married are in a better position to adopt mobile banking compared to other groups.

All other variables are not posing any impact on adoption of mobile banking.

2.7.4 Results of ATM users

For dependent variable ATM card use (Yes/No), the conduct of the Binary Logistic regression provided the following results:

Model Fitting:

At first different test associated with model fitting were checked followed by actual results.

Table 2.6.1 Omnibus Tests of Model Coefficients for ATM users

		Chi-square	df	Sig.
Step 1	Step	498.490	31	.000
	Block	498.490	31	.000
	Model	498.490	31	.000

Here in the model presented in Table 2.6.1, the p value is significant (.000 < .05) and hence we can conclude that there is a significant effect for the combined predictors on the outcome variable.

Table 2.6.2 Model Summary for ATM users

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	56.018[a]	.712	.950

From Table 2.6.2 the -2 Log Likelihood is 56.018[a], which is smaller in value indicating better fit and similarly the Nagelkerke R Square value is .950 also indicating good fit.

Table 2.6.3 Hosmer and Lemeshow Test for ATM users

Step	Chi-square	df	Sig.
1	.462	8	1.000

The Hosmer and lemeshow test of goodness of fit also indicating a good fit with value 1.000 >0.05 with chi square value 0.462.

From the results of the logistics regression with dependent variable ATM card use (Yes/No), presented in the Table A5 in the appendix shows that location, no of saving account, earners in the family (significant at 10 percent level), education level, frequency of banking transactions, marital status and income have significant effect on adoption of ATM card usage after conducting the Wald test.

For the variable ‘location’ the values from the appendix table A5 suggests that respondents who are from urban area are 6.3 times (odds ratio 6.321) more likely

to adopt ATM card compared to respondents who are from rural area. Thus people from urban area have a better chance in ATM adoption.

For the variable ‘ number of savings account’ the values from the appendix table A5 reveals that with an increases in number of savings account the chance of ATM card usage decreases by 0.125 times (odds ratio 0.125).

For the variable ‘number of earners in the family’ the results from Table A5 in appendix suggest that with increases in number of earners in the family a respondent is 2 times (odds ratio 2.128) more likely to adopt ATM card. Thus with increase in number of earners in the family the chance of ATM card adoption increases.

Education has a significant effect on adoption of ATM card. Categories such as ‘higher secondary education’, ‘graduate’, ‘and post graduate’ are significantly contributing towards ATM card adoption. The results from table A5 in appendix suggest that a respondent having ‘higher secondary education’ level are almost 4 times (odds ratio 3.991) more likely to adopt ATM card compared to the respondents who are below matriculation (reference category). Similarly, those with education graduate increases are almost 7 times (odds ratio 6.869) more likely to adopt ATM card compared to below matriculation respondents. Likewise, respondents who have post graduate qualifications are 4.6 times (odds ratio 4.595) more likely to adopt ATM card compared to respondents with below matriculation qualifications. Hence it means that respondents with higher qualification are more likely to adopt ATM card compared to lower educational qualification.

For 'frequency of banking transactions', it has been found that only category banking transactions 'once a week' is significant. The result from the table A5 in appendix suggests that respondents who do banking transactions once a week are 5 times (odds ratio 4.998) more likely to adopt ATM card compared to respondents doing banking transactions rarely (reference category). Thus respondents doing transaction at least once a week has higher chance of ATM card adoption compared to other categories.

All the income levels are found to be significant in adoption of ATM card. The results in table A5 in appendix reveals that respondents with income level 'less than or equal to Rs 20000' are 3 times (Odds Ratio 3.068) more likely to adopt ATM card compared to respondents having "income more than Rs 1000001' (reference category). Similarly those respondents who falls under income categories 'between Rs 200001 to Rs 500000' , between Rs 500001 to Rs 700000' and income between Rs 700001 to Rs 1000000' are respectively 7.8 times, 8.3 times and 15.5 times more likely to adopt ATM card compared to reference category. Thus increase in income level increases the chance of ATM card adoption.

2.7.5 Results of credit card users

For dependent variable Credit Card use (Yes/No), the conduct of the Binary Logistic regression provided the following results:

Model Fitting:

At first different test associated with model fitting were checked followed by actual results.

Table 2.7.1 Omnibus Tests of Model Coefficients for credit card users

		Chi-square	Df	Sig.
Step 1	Step	129.222	31	.000
	Block	129.222	31	.000
	Model	129.222	31	.000

Here in our model presented in Table 2.7.1, the p value is significant (.000 < .05) and hence we can conclude that there is a significant effect for the combined predictors on the outcome variable.

Table 2.7.2 Model Summary for credit card users

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	130.845[a]	.276	.577

From Table 2.7.2 the -2 Log Likelihood is 130.845[a], which is smaller in value indicating better fit and similarly the Nagelkerke R Square value is .577also indicating good fit.

Table 2.7.3 Hosmer and Lemeshow Test for credit card users

Step	Chi-square	df	Sig.
1	5.366	8	.718

The Hosmer and lemeshow test of goodness of fit in Table 2.7.3 also indicating a good fit with value 0.718>0.05 with chi square value 5.366.

From the results of the logistics regression with dependent variable Credit card use (Yes/No), presented in the Table A6 in the appendix shows that earners in the family, job level and income have significant effect on adoption of credit card usage after conducting the wald test.

For the variable earners in the family, with increase in number of earners in the family, the respondents are 2 times (odds ratio 2.217) more likely to adopt credit card. Thus with increase in earners of the family the chance of credit card adoption increases.

For the variable job level, blue collared worker and white collared workers are significantly contributing to credit card adoption. It is found that white collared workers are 3.6 times (odds ratio 3.60) more likely to adopt credit card compared to respondents in service category. Similarly blue collared are 5 times (odds ratio 5.244) more likely to adopt credit card compared to respondents in service category.

For the variable income, respondents in the category 'up to Rs 200000' and 'Rs 200001 to Rs 500000' are significantly contributing towards credit card adoption. Those respondents who are in the income category 'up to Rs 200000' and 'Rs 200001 to Rs 500000' are respectively almost 3 times (Odds Ratio 2.875) and 7 times (Odds Ratio 6.987) more likely to adopt credit card compared to people with income category 'more than Rs 1000000'. Hence people in income category up to Rs 200000' and 'Rs 200001 to Rs 500000' are more likely to adopt credit card compared to other income groups.

Rest all other variables seemed to be insignificant in adoption of credit card usage.

2.8 Conclusion

It has been seen that the socio economic factors are major contributing factor in adoption of technology. The study finds that socio economic factors and its impact in adoption of E-banking among salaried employees is in accordance with the E-banking adoption model mentioned earlier in the study.

The model had a probability function

$$Y = f(Z, \beta) + \varepsilon,\ Y = 0, 1.$$

Again we had $Pr(Y=1) = Pr(-\eta < U^*)$.

Keeping in view that E-banking is adopted (Y=1), we have $f(Z, \beta) + \varepsilon = 1$. Hence, the final adoption function can be explained as

$$f(Z, \beta) + \varepsilon = Pr(-\eta < U^*).$$

Where, Z are the socio economic factors like location of residence, number of earners in the family, education level, frequency of banking transaction and marital status which may impact E-banking adoption.

$$U^* = f\left(X_{E-banking}, t_{E-banking}; R\right) - f\left(X_{traditional\ banking}, t_{traditional\ banking}; R\right) - \delta$$

When the analysis was carried out for individual E-banking channels, the factors affecting the channels' adoption seemed to be slightly different. Internet banking adoption seemed to be influenced by number of members in the family and frequency of E-banking service. When we considered mobile banking, we found

that location, number of earners in the family, frequency of use of banking service, marital status are found to impact the adoption . As far as ATM card usage is concerned location, no of saving account, earners in the family, education level, frequency of banking transactions, marital status and income have significant effect on adoption of ATM card usage. Similarly, for credit card usage, number of earners in the family, job level and income seemed to be significantly contributing towards adoption of credit cards.

Table 2.8 Dependent Variables and Identified significant independent variables

Dependent variable	Identified significant independent variable
Electronic Banking (overall)	Location of residence, earners in the family, educational level, frequency of banking transaction and marital status.
Internet Banking	Number of members in the family and frequency of banking service.
Mobile Banking	Location of residence, number of earners in the family, frequency of banking transaction, marital status.
ATM card	Location of residence, number of saving account, number of earners in the family, education level, frequency of banking service, marital status and income.
Credit Card	Number of earners in the family, job level and income.

As far as the E-banking delivery channels are concerned, it has been observed that out of all E-banking users, the number of internet Banking users, mobile banking

users and credit card users are not very encouraging. It has also been found that those who are E-banking users, majority of them use ATM card. Thus, the financial sector should find strategies to diminish the variability in the usage of frequency of various E-banking Channels.

An interesting fact can be highlighted from the variable location of residence and adoption of E-banking channels. The rural urban divide seems to be similar between overall E-banking adoption and ATM card adoption but seemed to decrease in case of Mobile banking channel. The reason may be highlighted to the cause that rural areas have less number of ATMs installed compared to urban area and hence contributing to more rural urban divide as far as ATM adoption is concerned. Whereas the high penetration of mobiles and smart phones in rural areas at par with that of urban area may be resulting in increase in use of mobile banking among rural customers and thus contributing towards decreasing the rural urban divide.

As far as utility of the results are concerned, the bank management can apply different strategies in targeting the salaried class of people in terms of location of residence, earners in the family, educational level, frequency of banking transaction and marital status in order to promote and encourage usage of E-banking. For example, banks situated in urban areas are more likely to offer their customers internet banking than banks in non-urban areas. Banks in more densely populated areas may respond to greater customer demand for internet banking and to more intense competitive pressure from rival banks in the same market (Gupta, 2008). For the banking sustainability electronic form of banking has become

inevitable. Hence, banking organization looking for new customers should try to understand why the customers specifically the salaried employees do-not adopt E-banking or a particular channel(s). The information obtained in the study could be used to develop strategies to attract new customer and at the same time encourage use of all the channels of E-banking.