IMB 445

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BREAKING BARRIERS: MICRO-MORTGAGE ANALYTICS

It had been a long day at the small shop that Nareshbhai (name changed to protect identity) owned at the street corner and as the day drew to a close, his thoughts wandered back to the previous day's developments. Finally, Shubham Housing Development Finance Company (hereinafter "Shubham"), a housing finance company, was willing to consider his application for a home loan. Nareshbhai felt hopeful yet apprehensive; he wondered if his dream of building a house for his family would finally come true. His reservations were not unfounded. As a teenager, he had moved to the city of Ahmedabad from a neighboring village to seek better employment opportunities. Over time, he had managed to set up a petty shop where he sold daily provisions, condiments, and general merchandise. At the end of a good month, he would earn between INR 20,000 and 25,000 —good enough household income for his family of four to be able to afford a house. However, until the previous day, he had found it impossible to obtain a home loan from any of India's other housing finance companies. As a micro-entrepreneur, he fell outside the "conventional" segment of loan applicants at these financial companies. He rarely, if ever, used to maintain any accounts of his business, and hence, he had been unable to produce the documents required by these housing finance companies such as tax returns, income proof, or bank statements. However, Shubham had seemed different and he felt optimistic about building his dream home after all.

Ajay Oak, the chief operating officer (COO) of Shubham Housing Development Finance Company, knew that in India there were 20 million home loan aspirants similar to Nareshbhai, who worked in the informal sector and constituted about 80% of India's urban residents.[1] Even though financing affordable housing was one of India's biggest challenges, it also offered a remarkable opportunity for enterprising finance companies. For Ajay and his team, a key challenge in serving this customer group was to effectively evaluate the loan repayment ability of prospective clients in the absence of basic mortgage documentation. Ajay's strong belief in the creditworthiness of the low-income group made him realize that the key to business success was to quickly identify potential customers through cost-effective means. Moreover, with the proliferation of new players in this nascent and rapidly expanding sector, providing faster application assessment time and differential processing fees for creditworthy clients would be vital to gaining a competitive edge and securing greater market share.

FINANCING THE HOUSING ASPIRATIONS OF INDIA'S INFORMAL SECTOR

In India, several million low-income families reside in crowded localities and endure a life of hardship in poorly constructed houses with pitiful sanitary conditions. Hernando de Soto, the influential Peruvian economist regards the provision of housing facilities to such families as the fundamental avenue to economic success and an improved quality of life. Indeed, many of these families aspire to live in good quality, affordable houses, but securing a housing loan to realize their dreams has often proved to be exceedingly challenging.

With the traditional real estate sector experiencing a slowdown in India after 2009, real estate players rapidly invested in low-income housing projects ranging from INR 3 lakh up to INR 10 lakh (USD 1 = INR 62, as of November 2013). However, many of these low-income families were unable to access affordable mortgages from banking institutions and resorted to borrowing from money lenders whose interest rates were anywhere between 36% to 60% per annum.[2]

[1] Source: Ministry of Housing and Urban Poverty Alleviation, Government of India
[2] Source: Pawan Gulani, Head of Sales and Product, Shubham Housing Development Finance Company

Jitendra Rudravaram, Naveen Bhansali, Swetha Murthy and Sutirtha Roy prepared this case under the guidance of U. Dinesh Kumar, Professor of Quantitative Methods and Information Systems for class discussion. This case is not intended to serve as an endorsement, source of primary data, or to show effective or inefficient handling of decision or business processes.

Traditionally, banks and housing finance companies have viewed such applicants as high-risk profiles primarily because a vast majority of them lacked the basic documentation that would be necessary to even begin processing a loan application. Furthermore, these banks conventionally serve only high- or middle-income customers and have accordingly built their organizational capacity to cater to these market segments. Financing the low-income segment demands a complete shift from an archetypal document-based underwriting process to an interview-based on-field verification process. Such a process would put the financial institution right into the homes and workplaces of these customers, wherein the financial viability of a potential customer would be assessed through personal interviews, evaluation of the customer's workplace, and thorough field-based due diligence.

Conventional housing finance institutions, which were more adept at traditional methods of assessment based on income and identification documents, were dismally short of the expertise needed to competently assess these customers. These challenges continued to keep traditional housing finance companies apprehensive about lending to low-income applicants and underscored their perception of low-income customers as a high-risk segment. At the same time, they recognized that the inadequacies in their loan underwriting process not only increased social inequity but also resulted in lost opportunities.

In 2010, the market for mortgages in the low-income housing bracket comprised more than 20 million households and was worth USD 182 billion. Driven by this existing socio-financial opportunity, several new housing finance companies pioneered a "small ticket" loan product to address the market gap. These companies realized that most of the applicants from this category would be ineligible for a housing loan if the conventional approach of document-based evaluation were applied. To address this challenge, companies such as Shubham introduced a new loan origination process that relied on detailed, field-based verification instead of formal financial documentation.[3]

SHUBHAM HOUSING DEVELOPMENT FINANCE COMPANY: THE GENESIS AND RISE

Shubham Housing Development Finance Company commenced its lending operations in May 2011 through a single branch in New Delhi, with a vision to provide mortgage products and housing improvement loans to families that were excluded by traditional housing finance institutions. Led by Sanjay Chaturvedi as the CEO and Ajay Oak as the COO, Shubham became a pioneer in offering formal housing credit to low-income families from the informal sector and within 2 years had over 40 branches spread across several cities in India. In November 2012, Gurgaon-based Shubham raised an additional USD 7.8 million (approximately INR 50 crore) from venture capitalists, two years after the housing finance firm had first raised around USD 2 million (approximately INR 12.5 crore).[4] By September 2013, Shubham had disbursed loans amounting to over INR 125 crore to around 2,300 applicants. Shubham's operating model sought to transcend the document-based underwriting process and follow an interview-based approach in order to understand an applicant's income and expense flows. A visual flow diagram of Shubham's loan approval process is provided in **Exhibit 1**.

LOAN EVALUATION PROCESS AND OPPORTUNITIES FOR COMPETITIVE ADVANTAGE

The interview-based approach allowed Shubham to assess the applicants based on their daily or monthly cash earnings as observed by Shubham's staff at the applicant's workplace, instead of relying on formal documentation for proof of their income. This relaxation of the documentation norms enabled deserving applicants to obtain a loan for purchasing/building a house. Most of these customers were typically employed as petty shop owners, taxi drivers, or household help.

The interview-based field assessment would be conducted by a credit officer from Shubham who personally visits the applicant's residence and workplace to assess and verify the details provided by the applicant during the loan origination phase. The credit officer would then create a story about the applicant's life by asking questions about

[3] Source: *Micro Mortgages: A Macro Opportunity in Low-Income Housing Finance*. Monitor Inclusive Markets. 2010. The study was commissioned by the NHB, funded by the FIRST initiative, and supported by the World Bank. The detailed study is available in the public domain and is available for download at the NHB and Monitor websites.

[4] Source: Bruhadeeswaran, R. 2012. *Shubham Housing Development Finance raises $7.8M from Elevar, Helion, Others*. www.vccircle.com/news/2012/11/12/shubham-housing-development-finance-raises-78m-elevar-helion-others

his/her family, education, living conditions, income, expenses, liabilities, assets, work, and so on. In the instance of self-employed individuals, the credit officer would also spend a day with the applicant and observe the income and expenses incurred to create a Profit/Loss statement. Finally, the completed verification and assessment statement would result in a qualitative record of the person's ability to regularly service the loan. As expected, despite the benefits associated with field-based assessment, this method presents its own set of challenges for Shubham. The process of interviewing all customers irrespective of whether it resulted in a loan sanction increases the costs and the time expended on each customer. As per a 2010 study by Monitor on the Indian micro mortgage industry, the cost of originating a loan could sometimes be as high as 31% of the total transaction cost incurred.[3]

Moreover, the interview-based approach is a subjective evaluation of the customer's ability to service a loan. Therefore, the decision to approve or reject a loan is dependent on Shubham's field-based credit officers who would assess a customer's loan repayment ability. A key business assessment is thus hinged on the credit officer's skill and subjective decision-making abilities. Comparing such decisions across different branches and field staff members in order to ensure consistency across branches also presents a significant challenge to Shubham's scale-up strategy. Often, the process of interviewing the candidates, verifying their credibility from third-party sources, and preparing the interview report leads to an extended loan processing time. Reducing this lead time would allow Shubham to communicate its decisions to prospective customers quicker, thus serving them much better.

Shubham's customers range from contractual employees with the government to grocery vendors, from auto rickshaw drivers to semi-skilled laborers. These applicants are in the age group of 22 to 63 years; they hail from different parts of the country and include school dropouts as well as post-graduates. Thus, Shubham's informal sector customers belong to a wide socioeconomic and demographic pool. A better understanding of these customer groups would enable Shubham to target its marketing efforts towards those customer segments that would lead to faster loan processing.

Shubham's data acquisition and collection processes at every stage of applicant assessment are among its greatest sources of competitive advantage. Ajay envisioned that an application scoring model built using the data generated from the field-level interactions would enhance decision making at the branch level.

The aforementioned Monitor study on micro mortgage sector reports that as per industry estimates, for a loan of INR 400,000, loan origination would cost INR 8,000, which constitutes 31% of the total transaction cost and 2.8% of the total loan disbursed. In addition to the loan origination cost, a non-performing asset (NPA) provision of INR 4,000 and a loan servicing cost of INR 13,844 brings the total transaction cost[2] to INR 25,844 (**Exhibit 2**). Upon sanction of the loan, the loan applicant would be charged a non-refundable amount equivalent to 2.5% of the sanctioned amount, in this instance, INR 10,000 towards loan processing fees. Evaluation of the loan sanction probability early in the process by the credit team could reduce field costs—the 31% cost component incurred in every transaction—by identifying creditworthy customers before the credit officer's visit (**Exhibit 3).** The product team could also make the product more competitive by offering differential loan processing charges to high potential clients (**Exhibit 4**).

Additionally, the sales team could reduce the operation costs that results from pursuing all prospective leads and could source better clients from demand-side aggregators as the business grew. The model would also reduce incorrect sanctions of more risky loan applications owing to subjective evaluations made by credit officers and would thereby help the standardization of decision making and reporting across nationwide branches.

DATA ANALYSIS

For the application scoring model, Ajay's analytics team acquired field-level data consisting of variables collected from each applicant (**Exhibit 5**). In addition to the socioeconomic variables (such as age, marital status, education, housing situation, income, expenses, loan amount requested, and so on) that were gathered from the application forms, Ajay's team calculated the standard mortgage ratios for each applicant. These ratios were Installment to Income Ratio (IIR), Installment to Disposable Income Ratio (IAR), Fixed Obligation to Income Ratio (FOIR), Loan to Value Ratio (LTV), and Loan to Cost Value Ratio (LVR) (**Exhibit 6**).

These ratios helped to capture important factors such as the ability of an applicant to repay debt, the proportion of property value sought as loan, and so on. Since these ratios are used extensively in processing applications, these were included in the dataset while building the scoring models in order to ascertain whether these ratios had a higher significance than the constituent individual variables.

The techniques of Chi-squared Automatic Interaction Detection (CHAID) and binomial logistic regression were employed to predict the loan sanctions. **Exhibit 7** contains the Tier classification of Indian cities. The CHAID model is depicted in **Exhibit 8** and the classification results obtained through the model for the training and the validation datasets are shown in **Exhibits 9** and **10**, respectively. **Exhibit 11** contains a sample of 100 applications used for testing the CHAID model. The output of a logistic regression model built by Keerthana, a junior analyst at Shubham is provided in **Exhibit 12(i)** and **(ii)**. Siddharth, a senior analyst at Shubham, built a slightly different logistic regression model whose output is given in **Exhibit 13**. Socio-economic details of two prospective applicants, Ahmed and Jagadish are provided in **Exhibit 14**. Classification results obtained for the training dataset using the logistic regression model built by Siddharth at different cutoff values are presented in **Exhibit 15**.

Exhibit 1

Shubham's Loan Approval Process

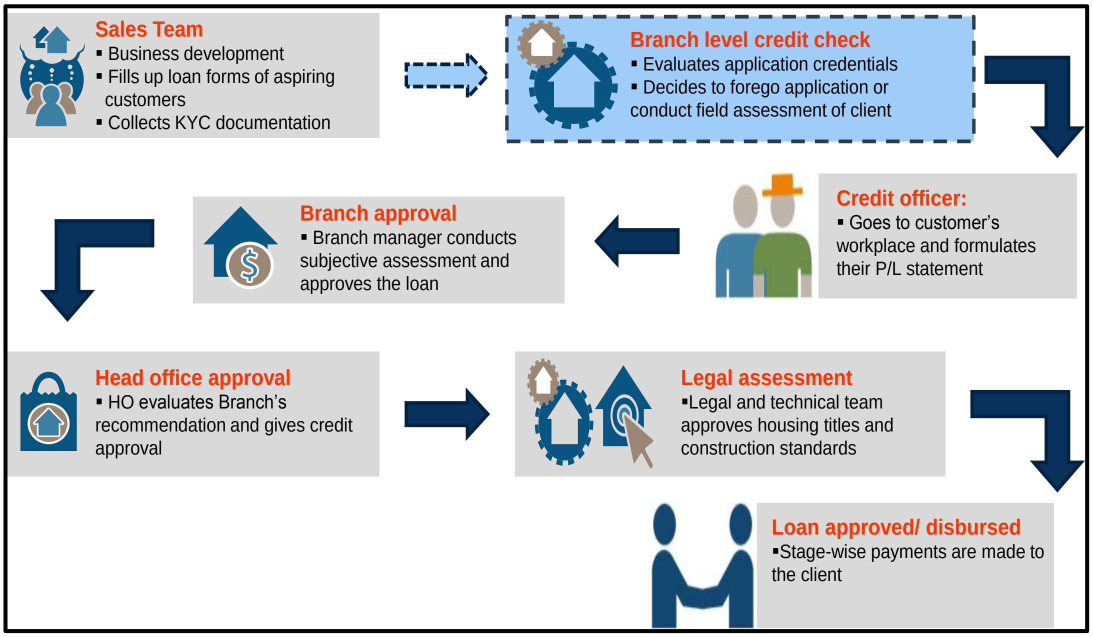
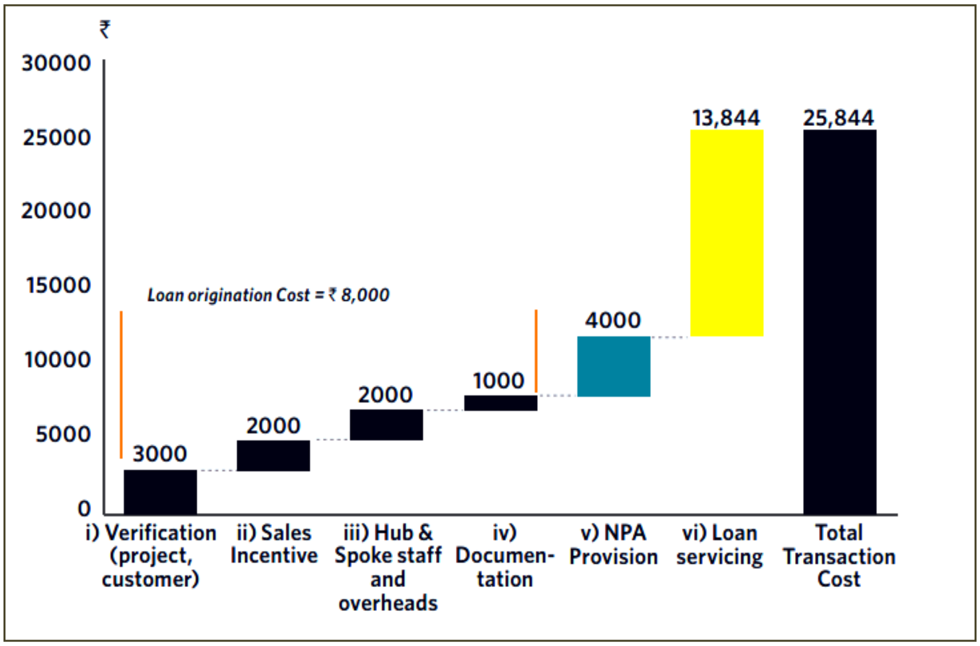


Exhibit 2

Cost Split-Up for an INR 4 Lakh Loan at ROI 14% and 10% Cost of Capital



Source: Monitor Inclusive Markets (2010)

Exhibit 3

Impact of Cost Reduction

Cost components	Current	Model application
Loan requested	4,00,000	4,00,000
Loan origination cost	8,000	4,500
Total transaction cost	25,844	22,844
% of transaction cost	6.46%	5.59%
% Origination cost vs. Transaction cost	30.95%	20.14%

Current Situation: For a rejected customer loan request of **4 lakh** @ **14%** ROI
Loan origination: INR **8,000** (3,000 for client and project verification + 2,000 for sales incentives + 2,000 for staff and overhead expenses +1,000 for documentation
Other costs = 0
Total cost = 8,000

On applying analytical model: For a rejected customer loan request of **4 lakh** @ **14%** ROI
Loan origination: INR **4,500** (1,000 for client and project verification + 1,000 for sales incentives + 2,000 for staff and overhead expenses + 500 for documentation)
Other costs = 0
Total cost = INR 4,500

Source: Monitor Inclusive Markets (2010)

Exhibit 4

Illustrative Example of Differential Processing Fee

Identical fee structure			
Customer	Customer 1	Customer 2	Customer 3
Loan amount required	400,000	400,000	400,000
Processing rate charged	2.50%	2.50%	2.50%
Processing fee charged	10000	10000	10000
Total processing fee	30000		
Differential fee structure			
Customer	Customer 1	Customer 2	Customer 3
Applicant score	0.95	0.85	0.75
Loan requested	400,000	400,000	400,000
Processing rate charged	2%	2.50%	3%
Processing fee charged	8000	10000	12000
Total processing fee	30000		

Note: Classification of sanctioned customers was highest when their probabilities of sanction were greater than 0.9 (Probability of sanctions > 0.9 customers => More sanctions and less rejections). From a strategic point of view, these customers could be offered a lower processing fee as compared to the rest of the applicants.

Exhibit 5

Data Variables

Variable	Definition
ID	Unique Identifier for each application
Decision	Credit decision taken for the applicant 1 = Sanction, 0 = Reject
Build_Selfcon	Variable to indicate whether applicant seeks a home loan for self-construction or a builder-promoted project
Selfcon_code	If Build_Selfcon = 'Self Construction', then Selfcon_code = 1; if Build_Selfcon = 'Builder', then Selfcon_code = 0
Tier	City tier where the loan was sought. Tier-1 = Major City, Tier-2 = Minor City, Tier-3 = Town/Village
Tier_1	If Tier = ‘Tier-1’, Tier_1 = 1; else Tier_1 = 0
Tier_2	If Tier = ‘Tier-2’, Tier_2 = 1; else Tier_2 = 0
Accommodation_Class	Variable to indicate whether applicant resides currently in rented or non-rented premises
Accoclass	If Accommodation_Class = 'Rented', Accoclass = 1, else Accoclass = 0
Loan_Type	Variable to indicate if loan was sought for Home loan or Home Improvement loan
Loantype	If Loan_Type = 'Home _Loan', Loantype = 1; else Loantype = 0
Gender	Applicant's Gender
Sex	If Gender = 'Male', Sex = 1; else Sex=0
Employment_Type	Variable to indicate whether the applicant was salaried or self-employed
Etype	If Employment_Type = 'Self_Employed', Etype = 1; else Etype = 0
doc_proof_inc	Indicates whether the applicant submitted documentary proof of income
Docprf	If doc_proof_inc = 'Y', Docprf = 1; else Docprf = 0
Marital_Status	Indicates if applicant is married or single currently
Marstat	If Marital_Status = 'Married', Marstat = 1; else Marstat = 0
Employer_Type	Applicant's Employer's category (Business, Corporate, Government, Ind/Small Business)
Emp_type_1	If Employer_Type = 'Business', Emp_type_1 = 1; else Emp_type_1 = 0
Emp_type_2	If Employer_Type = 'Govt', Emp_type_2 = 1; else Emp_type_2 = 0
Emp_type_3	If Employer_Type = 'Corporate', Emp_type_3 = 1; else Emp_type_3 = 0
Education_Class	Education of the applicant
Educlass_2	If Education_Class = 'GRADUATE+', Educlass_2 = 1; else Educlass_2 = 0
Educlass_1	If Education_Class = 'UNDERGRADUATE', Educlass_1 = 1; else Educlass_1 = 0
Mode_of_origin_class	The source from which the application originated
Oriclass_1	If mode_of_origin_class = 'Reference', Oriclass_1 = 1; else Oriclass_1 = 0
Oriclass_2	If mode_of_origin_class = 'Own database field visit', Oriclass_2 = 1; else Oriclass_2 = 0
eom_25	Variable to indicate whether the application was received after the 25th of the month

Exhibit 5 (Contd.)

Variable	Definition
oldemi_d	Variable to indicate if applicant had old loans
bs_d	Variable to indicate if applicant has bank savings
Age	Age of applicant
Yrsadd	Years in current residential address
Yrsjob	Years in current job
Expen	Monthly expenses of applicant
Totinc	Monthly income of applicant
Dispinc	Total monthly income - Total monthly expenses
Marval	Market value of the property for which loan is sought
Oldemi	EMI for earlier loans that the applicant pays every month
Loanreq	Loan amount requested by applicant
Term	Term for the loan
Dwnpay	Down payment by applicant
Banksave	Bank saving of applicants
Calcemi	EMI calculated for the applicant's requested loan amount
IIR	Calcemi/Monthly total income
IAR	Calcemi/Monthly disposable income
FOIR	(Calcemi + Oldemi)/Total monthly income
LTV	Total loan requested/Market Value
LVR	Total loan requested/Property registered value
dwnp_prop	Dwnpay / (Dwnpay + Loanreq)
mfoir_p	((Oldemi + Calcemi) * 100) Dispinc
dwnp_prop_p	Dwnp_prop * 100
dispinc_s	Dispinc/10000
marval_s	Marval/1000000
loanreq_s	Loanreq/100000
banksave_s	Banksave/10000
calcemi_s	Calcemi/10000
oldemi_s	Oldemi/10000
Tier_2XAccoclass	Interaction variable of Tier_2 & Accoclass

Exhibit 6

Standard Mortgage Ratios

IIR	$\frac{\text{Equated Monthly Installments (EMI)}}{\text{Total Household Income}}$
IAR	$\frac{\text{Equated Monthly Installments (EMI)}}{\text{Disposable Income}}$ Disposable Income $=$ Total Household Income $-$ Total Expenses
LTV	$\frac{\text{Total Loan Requested}}{\text{Market Value of Property}}$
LVR	$\frac{\text{Total Loan Requested}}{\text{Property Value}}$ Property value is registered value of property at the municipality
FOIR	$\frac{\text{EMI} + \text{Ongoing Loan EMI}}{\text{Total Household Income}}$

Exhibit 7

Tier Classification of Indian Cities

Tier classification	City	Tier classification	City	Tier classification	City
1	Bangalore	2	Vadodara	2	Aurangabad
1	Chennai	2	Ludhiana	2	Srinagar
1	Delhi	2	Agra	2	Bhilai
1	Hyderabad	2	Meerut	2	Rajahmundry
1	Kolkata	2	Nashik	2	Kakinada
1	Mumbai	2	Faridabad	2	Nellore
1	Ahmedabad	2	Varanasi	2	Solapur
2	Bhopal	2	Jabalpur	2	Ranchi
2	Kanpur	2	Jamshedpur	2	Guwahati
2	Jaipur	2	Allahabad	2	Gwalior
2	Nagpur	2	Amritsar	2	Chandigarh
2	Lucknow	2	Indore	2	Patiala
2	Patna	2	Gorakhpur	2	Jodhpur
2	Pune	2	Hubli-Dharwad	2	Tiruchirapalli
2	Visakhapatnam	2	Raipur	2	Salem
2	Vijayawada	2	Mysore	2	Trivandrum
2	Kochi	2	Mangalore	2	Rajkot
2	Madurai	2	Belgaum	2	Cuttack
2	Coimbatore	2	Guntur	2	Amravati
2	Warangal	2	Bhubaneswar	2	Pondicherry
2	Surat	2	Bhavnagar	3	All other cities
2	Asansol				

Source: Sixth Central Pay Commission of India

Exhibit 8

Chi-Squared Automatic Interaction Detection (CHAID) Model

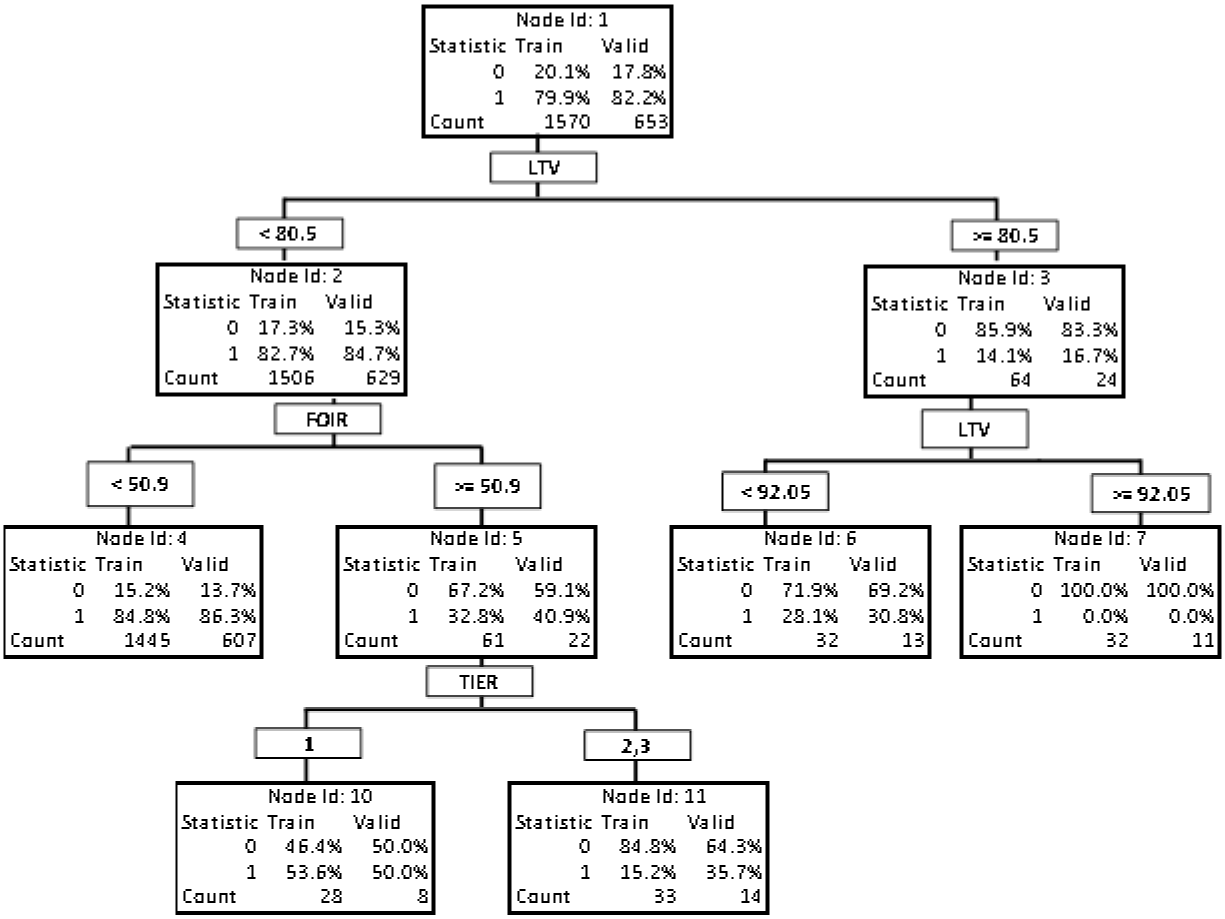


Exhibit 9

Classification Results of CHAID Model for Training Dataset

Classification Table: Training		
Target	Outcome	Frequency count
0	0	83
1	0	14
0	1	232
1	1	1241

Sensitivity	98.8%
Specificity	26.3%

Exhibit 10

Classification Results of CHAID Model for Validation Dataset

Classification Table: Validation		
Target	Outcome	Frequency count
0	0	29
1	0	9
0	1	87
1	1	528

Sensitivity	98.3%
Specificity	25%

Exhibit 11

Sample Dataset Used to Test the CHAID Model

Id	Decision	Tier of City	Age	Yrsadd	Oldemi	FOIR	LTV
DEL-S6QA-442656	Reject	1	37	13	0	32.00	57.00
GUJ-KE2E-383829	Reject	1	45	9	0	25.65	177.78
MDG-TR7G-885286	Reject	3	27	2	12679	56.54	67.00
MDG-EA6U-239956	Reject	3	32	5	0	31.00	89.00
GUJ-CHA6-377655	Reject	1	28	6	0	51.00	71.00
DEL-CRU4-638996	Reject	1	39	8	0	30.78	66.67
RAJ-CU3A-435927	Reject	2	37	5	2240	49.64	73.00
SHB-PRU8-975396	Reject	3	37	6	0	49.00	80.00
NAG-HE5R-459425	Reject	2	34	6	0	32.00	25.00
GUJ-9ASP-257984	Reject	1	31	25	0	54.00	80.00
MDG-SE8U-743796	Reject	3	45	2	0	47.00	59.00
FBD-GUH2-767994	Reject	2	35	10	0	34.00	72.00
DEL-5UBR-632944	Reject	1	29	10	0	52.07	145.45
SAH-P6AW-477253	Reject	3	50	1	0	34.00	62.00
GUJ-9RAS-857253	Reject	1	40	4	0	35.63	120.94
JAM-4RES-776444	Reject	3	30	28	40000	30.99	50.00
GUJ-ME7A-946978	Reject	1	24	23	0	38.00	85.00
VAD-QA7H-459898	Reject	2	27	10	0	27.00	40.00
RAJ-CHA5-963229	Approve	2	43	10	0	49.00	78.00
SRT-CR8J-295523	Approve	2	33	6	0	31.00	51.00
GUJ-9HUS-878464	Approve	1	28	2	0	47.00	49.00
SHB-9UDA-632993	Approve	3	33	10	0	38.00	26.00
MDG-WE7R-964695	Approve	3	41	1	0	22.00	40.00
SHB-VUH7-746557	Approve	3	47	14	0	37.00	62.00
SRT-6RES-429394	Approve	2	32	1	0	42.00	67.00
SRT-WE2U-246244	Approve	2	39	3	0	37.00	61.00
GUJ-PR8Z-554775	Approve	1	52	4	0	48.00	35.00
MRT-SP2P-623473	Approve	2	41	10	0	14.00	29.00
GUJ-CRA8-753769	Approve	1	36	3	2455	43.86	46.00
SHB-Q2FA-784777	Approve	3	36	10	0	47.00	80.00
GUJ-2RAH-276674	Approve	1	34	31	0	35.00	23.00
PUN-9ADA-922444	Approve	2	27	3	0	50.00	65.00
SRT-7AWR-894639	Approve	2	30	3	0	39.00	53.00
IDR-K5BR-529575	Approve	2	27	10	0	44.00	24.00
SHB-TR5G-853778	Approve	3	32	20	5495	43.39	80.00
AMR-PET7-268923	Approve	2	27	26	8743	47.10	48.00
SHB-J8TE-869465	Approve	3	33	3	0	35.00	62.00

Exhibit 11 (Contd.)

Id	Decision	Tier of City	Age	Yrsadd	Oldemi	FOIR	LTV
NAG-SUM5-824386	Approve	2	32	30	0	41.00	77.00
SRT-MEP2-939449	Approve	2	32	4	0	47.00	63.00
GUJ-B3SP-584592	Approve	1	39	7	3310	47.67	80.00
AJM-DR3F-728347	Approve	3	49	3	0	23.00	45.00
SRT-GEX5-278492	Approve	2	41	3	0	42.00	32.00
MDG-TR8Y-794363	Approve	3	28	7	4772	45.79	39.00
SRT-V7MU-562553	Approve	2	26	1	0	38.00	66.00
SRT-FRE8-682823	Approve	2	35	4	0	47.00	55.00
SHB-Y5DR-546357	Approve	3	35	1	0	45.00	27.00
SRT-PR5B-887235	Approve	2	31	2	0	14.00	46.00
MDG-P8UH-689386	Approve	3	39	6	6741	49.06	61.00
MRT-HU8A-244932	Approve	2	52	1	0	47.00	36.00
SHB-AI9Q-623595	Approve	3	29	8	0	25.00	79.00
GUJ-SWA7-532964	Approve	1	48	4	0	31.00	12.00
FBD-S2UC-952959	Approve	2	30	3	0	30.00	42.00
PUN-2HAS-626445	Approve	2	29	2	2116	50.05	67.00
RAJ-TR4T-834863	Approve	2	24	2	0	43.00	63.00
DEL-TRA3-376247	Approve	1	40	10	0	23.00	62.00
DEL-BE3P-484634	Approve	1	33	11	0	43.00	50.00
GUJ-DUC2-753522	Approve	1	35	2	0	40.00	53.00
NAS-TEQ8-493685	Approve	2	25	5	0	45.00	36.00
GUJ-8UNA-562324	Approve	1	47	0	0	33.00	73.00
GUJ-8RAY-382542	Approve	1	35	5	0	7.00	30.00
SRT-P9UF-599895	Approve	2	33	4	0	36.00	53.00
SHB-QEC9-262767	Approve	3	31	2	20220	44.60	80.00
DEL-F9SP-826567	Approve	1	40	20	0	19.00	27.00
MDG-Y8PH-666948	Approve	3	33	30	0	44.00	55.00
SHB-WR8C-828893	Approve	3	33	5	0	21.00	62.00
NAS-H7BR-796623	Approve	2	30	10	0	46.00	33.00
MDG-VA5R-522867	Approve	3	41	1	0	41.00	28.00
GUJ-PHE2-945563	Approve	1	33	9	0	43.00	55.00
SHB-3ATH-365745	Approve	3	27	2	0	50.00	50.00
RAJ-S5UP-432944	Approve	2	33	8	0	49.00	58.00

Exhibit 11 (Contd.)

Id	Decision	Tier of City	Age	Yrsadd	Oldemi	FOIR	LTV
SHB-GAJ5-656633	Approve	3	27	3	17349	55.41	33.00
DEL-6HAP-992534	Approve	1	39	2	0	9.00	71.00
SRT-XER8-873652	Approve	2	34	1	7141	49.12	22.00
IDR-7HUX-947934	Approve	2	43	4	0	34.00	32.00
MRT-Y5TH-366839	Approve	2	31	2	0	39.00	71.00
SHB-7UWA-942266	Approve	3	48	3	0	40.00	37.00
SRT-FEW6-377924	Approve	2	42	2	0	46.00	56.00
SRT-HU4H-759456	Approve	2	28	8	0	44.00	24.00
IDR-PR2B-373527	Approve	2	54	20	0	27.00	89.00
RAJ-NE5W-936659	Approve	2	51	49	0	49.00	42.00
GUJ-G2BR-585643	Approve	1	25	20	0	31.00	46.00
VAD-9EGU-733365	Approve	2	39	1	0	31.00	43.00
DEL-TR5G-982679	Approve	1	57	24	0	39.00	62.00
SRT-CEV2-858888	Approve	2	35	1	11369	49.55	52.00
SHB-7EFR-562262	Approve	3	45	1	0	26.00	60.00
VAD-5REP-436572	Approve	2	34	30	1493	44.73	79.00
GUJ-TR2X-454675	Approve	1	37	1	2172	46.89	69.00
MRT-FR4H-849474	Approve	2	34	5	0	39.00	57.00
SRT-VAG4-472429	Approve	2	25	8	0	46.00	47.00
DEL-SP7T-869623	Approve	1	60	33	0	21.00	14.00
SHB-9ABR-357338	Approve	3	31	2	0	40.00	50.00
DEL-6HED-235585	Approve	1	28	1	0	38.00	75.00
PUN-STA6-298789	Approve	2	37	25	1558	44.41	42.00
DEL-S3ET-655923	Approve	1	32	5	0	28.00	80.00
AJM-BRU8-457322	Approve	3	38	8	0	49.00	34.00
DEL-REC6-289437	Approve	1	42	2	0	44.00	67.00
RAJ-SPE8-423236	Approve	2	42	2	0	50.00	71.00
IDR-THE9-644793	Approve	2	40	15	0	33.00	44.00
JAM-NU9R-969974	Approve	3	27	24	0	43.00	47.00
GUJ-G6VU-427765	Approve	1	33	20	0	37.00	52.00

Exhibit 12(i)

Logistic Regression Output Model-1

Analysis of Maximum Likelihood Parameter Estimates			
Parameter	**DF**	**Parameter Estimate**	**Standard Error**
Intercept	1	6.2404	1.1965
Tier_1	1	0.3931	0.1815
Tier_2	1	0.6801	0.1842
AccoClass	1	0.6310	0.1689
LoanType	1	0.7162	0.3507
Sex	1	0.4159	0.2881
Etype	1	-0.2169	0.1839
Doc_pf	1	0.1603	0.1957
OldEMI_d	1	0.7007	0.2445
BankSave_d	1	0.4607	0.3348
Age	1	-0.0034	0.0109
YrsAdd	1	0.0030	0.0076
YrsJob	1	-0.0053	0.0113
DispInc	1	0.0112	0.0739
MarVal	1	0.3998	0.3408
Term	1	0.0016	0.0047
BankSave_s	1	0.0493	0.0250
CalcEMI_s	1	-0.7151	1.3868
Dwnp_prop	1	-0.0764	0.0080
IAR	1	0.0219	0.0050
LTV	1	-0.0678	0.0093
Loan_req	1	0.0000	0.0000

Exhibit 12(ii)

Variance Inflation Output Model-1

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Tolerance	Variance Inflation
Intercept	1	1.05048	0.1244	8.44	<.0001		
Tier_1	1	0.05225	0.0240	2.18	0.0295	0.65819	1.51931
Tier_2	1	0.08545	0.0232	3.68	0.0002	0.64912	1.54054
AccoClass	1	0.08489	0.0208	4.09	<.0001	0.75814	1.31901
LoanType	1	0.09950	0.0458	2.17	0.0301	0.61813	1.61778
Sex	1	0.06601	0.0323	2.05	0.041	0.97920	1.02124
Etype	1	-0.03005	0.0226	-1.33	0.1834	0.64507	1.55021
Doc_pf	1	0.01594	0.0230	0.69	0.4892	0.77687	1.28721
OldEMI_d	1	0.08635	0.0272	3.17	0.0015	0.97507	1.02556
BankSave_d	1	0.09967	0.0327	3.05	0.0024	0.72413	1.38096
Age	1	-0.00098	0.0013	-0.76	0.4464	0.69425	1.44040
YrsAdd	1	0.00037	0.0010	0.38	0.7071	0.76428	1.30842
YrsJob	1	-0.00046	0.0014	-0.33	0.7422	0.65718	1.52165
DispInc	1	-0.00670	0.0102	-0.66	0.5108	0.37605	2.65922
MarVal	1	0.01829	0.0235	0.78	0.4366	0.34456	2.90225
Term	1	0.00053	0.0006	0.90	0.3698	0.17286	5.78502
BankSave_s	1	0.00117	0.0007	1.77	0.0766	0.73061	1.36871
CalcEMI_s	1	0.03869	0.1803	0.21	0.8301	0.01906	52.46589
Dwnp_prop	1	-0.00643	0.0006	-10.07	<.0001	0.72129	1.38640
IAR	1	0.00248	0.0006	4.07	<.0001	0.47786	2.09266
LTV	1	-0.00649	0.0006	-10.34	<.0001	0.42528	2.35139
Loan_req	1	-0.0000001789	0.0000	-0.62	0.5358	0.01739	57.50431

Exhibit 13

Logistic Regression Output Model-2

Analysis of Maximum Likelihood Parameter Estimates					
Parameter	**DF**	**Parameter Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	6.3699	0.76700	68.9723	<.0001
Tier_1	1	0.4183	0.17940	5.4366	0.0197
Tier_2	1	1.0342	0.24230	18.2181	<.0001
AccoClass	1	0.8272	0.18330	20.3655	<.0001
LoanType	1	0.8804	0.29190	9.0969	0.0026
OldEMI_d	1	0.6990	0.24430	8.1867	0.0042
BankSave_d	1	0.4695	0.33910	1.9170	0.1662
BankSave_s	1	0.0522	0.02620	3.9695	0.0463
CalcEMI_s	1	-0.8560	0.22260	14.7876	0.0001
Dwnp_prop_p	1	-0.0749	0.00782	91.7382	<.0001
IAR	1	0.0235	0.00356	43.5748	<.0001
LTV	1	-0.0751	0.00694	117.1011	<.0001
Tier_2XAccoClass	1	-0.7147	0.32690	4.7799	0.0288

Exhibit 14

Socio-economic Details of Two Prospective Applicants

Applicant Name	Ahmed	Jagadish
Tier of city	3	2
Accoclass	Rented	Non-Rented
Loantype	Home Loan	Home Improvement
dwnpay_prop	18.7	21.03
Calculated EMI Amount	3221	4172
IAR	31	47
LTV	51	74
Old EMI Amount	0	0
Bank Savings	0	0

Exhibit 15

Classification values at various cut off probabilities using Logistic Regression Model-2

Cut-off	TP	TN	FP	FN
0.05	1255	18	297	0
0.1	1255	22	293	0
0.15	1254	28	287	1
0.2	1252	33	282	3
0.25	1249	37	278	6
0.3	1245	45	270	10
0.35	1239	47	268	16
0.4	1231	60	255	24
0.45	1219	72	243	36
0.5	1207	85	230	48
0.55	1184	109	206	71
0.6	1159	132	183	96
0.65	1118	155	160	137
0.7	1081	183	132	174
0.75	998	217	98	257
0.8	908	237	78	347
0.85	772	264	51	483
0.9	616	292	23	639
0.95	391	307	8	864
1	0	315	0	1255