An Introduction to Digital Credit:
Resources to Plan a Deployment

3 June 2016

Welcome!

This introductory course is designed for those who aim to design and deliver digital credit: Banks, payments providers, mobile operators, microfinance lenders or third party fintech firms. Donors, regulators and policy makers will also find this a useful introduction.

A few notes on the content:

- This provides a basic introduction to digital credit, enough to begin planning a service.
- Many readers will have ideas and ways to improve the content, and we welcome this.
- There is an excel financial model and presenter notes that accompany the main PDF file which can be accessed at the email address below.

CGAP has built this introductory content based on field observations and learnings from existing deployments. There have also been critical contributions from consultants. Special note of thanks to Jamal Rahal (jamal.rahal@hotmail.com) who has been a teacher on this topic for many. We have done our best to reflect his wisdom here. Jacobo Menajovsky led the credit scoring section. Martha Casanova (mecasanov@gmail.com) shaped the accompanying financial model. There are many others who have contributed; we are especially grateful to the entrepreneurs who are testing digital credit services and who share their experiences with us.

The final responsibility for the content rests with CGAP. For comments or to request more materials (including the financial model), please write to cgap@worldbank.org

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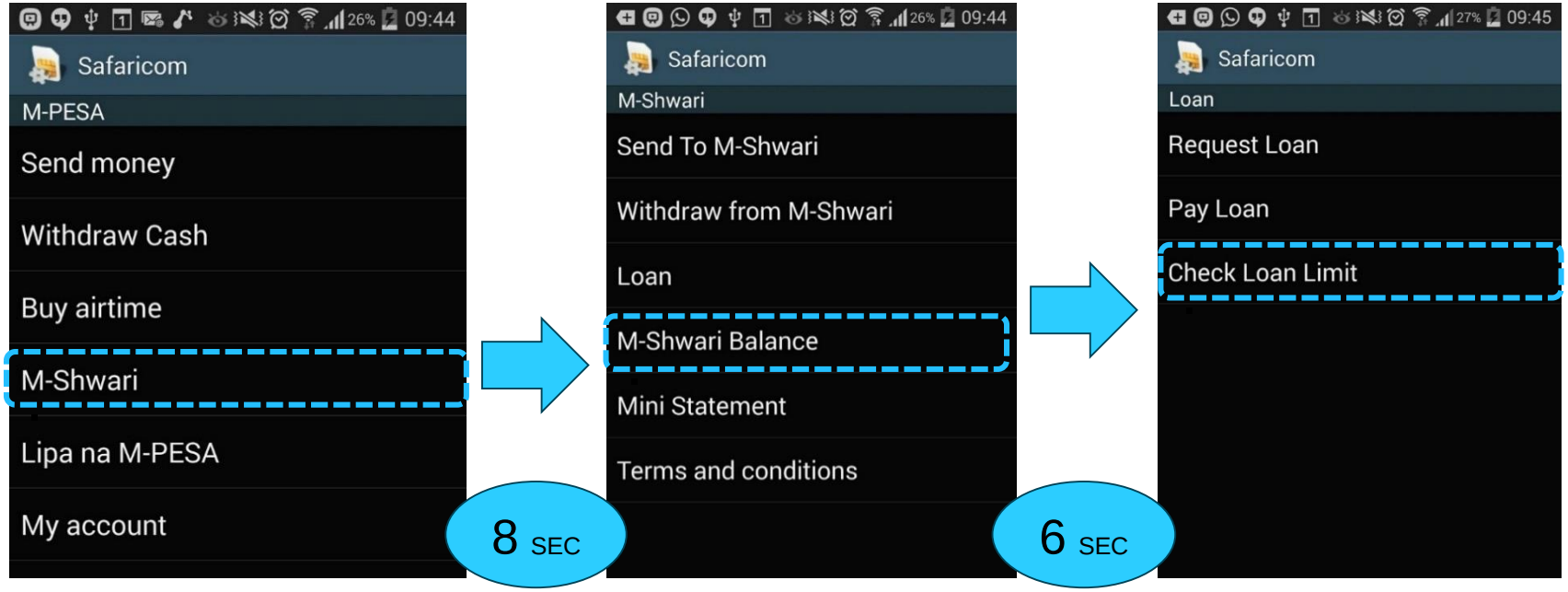
Example:

Providers	Safaricom, cba
Country/Launch	**Kenya** (2012)



Turn around time on account activation

Turn around time on transaction processing

A Few Definitions

PHOTO CREDIT: Wim Opmeer, 2012 CGAP Photo Contest

Some Definitions

Digital Finance: Financial services delivered primarily over digital infrastructure (mobile or Internet) with a low use of traditional brick-and-mortar branches.

Branchless Banking: Services delivered outside of bank branches often through the use of agents. Sometimes this term is used interchangeably with Digital Finance

Mobile Financial Services: Financial services delivered digitally over a mobile phone (a subset of digital finance). Sometimes this term is used interchangeably with Digital Finance.

Digital Credit: Product offered under digital finance. Lending that involves limited in-person contact, leveraging digital infrastructure.

Mobile Money: Basic payment services delivered over a small transaction account on the mobile phone.

Key Attributes of Digital Credit

CONVENTIONAL CREDIT		DIGITAL CREDIT
Days	TIME TO MAKE DECISIONS	Instant
People's Judgment	RISK MANAGEMENT PROCESS	Automated
In Person	SENDING INFORMATION AND PAYMENTS	Remote

Key Attributes of Digital Credit

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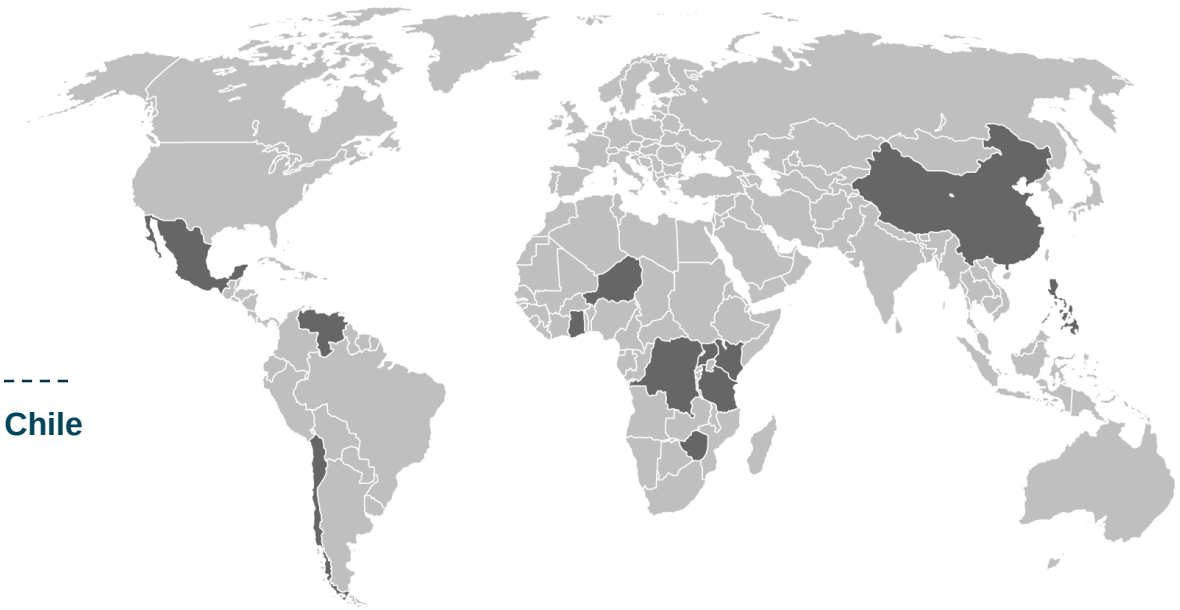
Digital Credit a Global Trend



Mexico

KONFÍO
kubo financiero

China

蚂蚁金服 ANT FINANCIAL
Tencent 腾讯

Venezuela and Chile

TIENDA PAGO

Philippines

Mynt A FRESH LOOK AT MONEY
AMP ADVANCED MERCHANT PAYMENTS

Kenya

M-Shwari
branch
KCB M-PESA ACCOUNT
KOPO KOPO
inVenture
Saida
Equitel

Tanzania

nimetimiza loans at your fingertips
cba m-pawa

Zimbabwe

ECOCASHLOANS

DRC, Niger, Rwanda, Uganda

airtel

Ghana

airtel

Variety of Digital Credit Approaches

1: Direct to individual

- Credit risk on individual
- Initially reliant on alternative data
- Track record builds, shifts to behavioral data

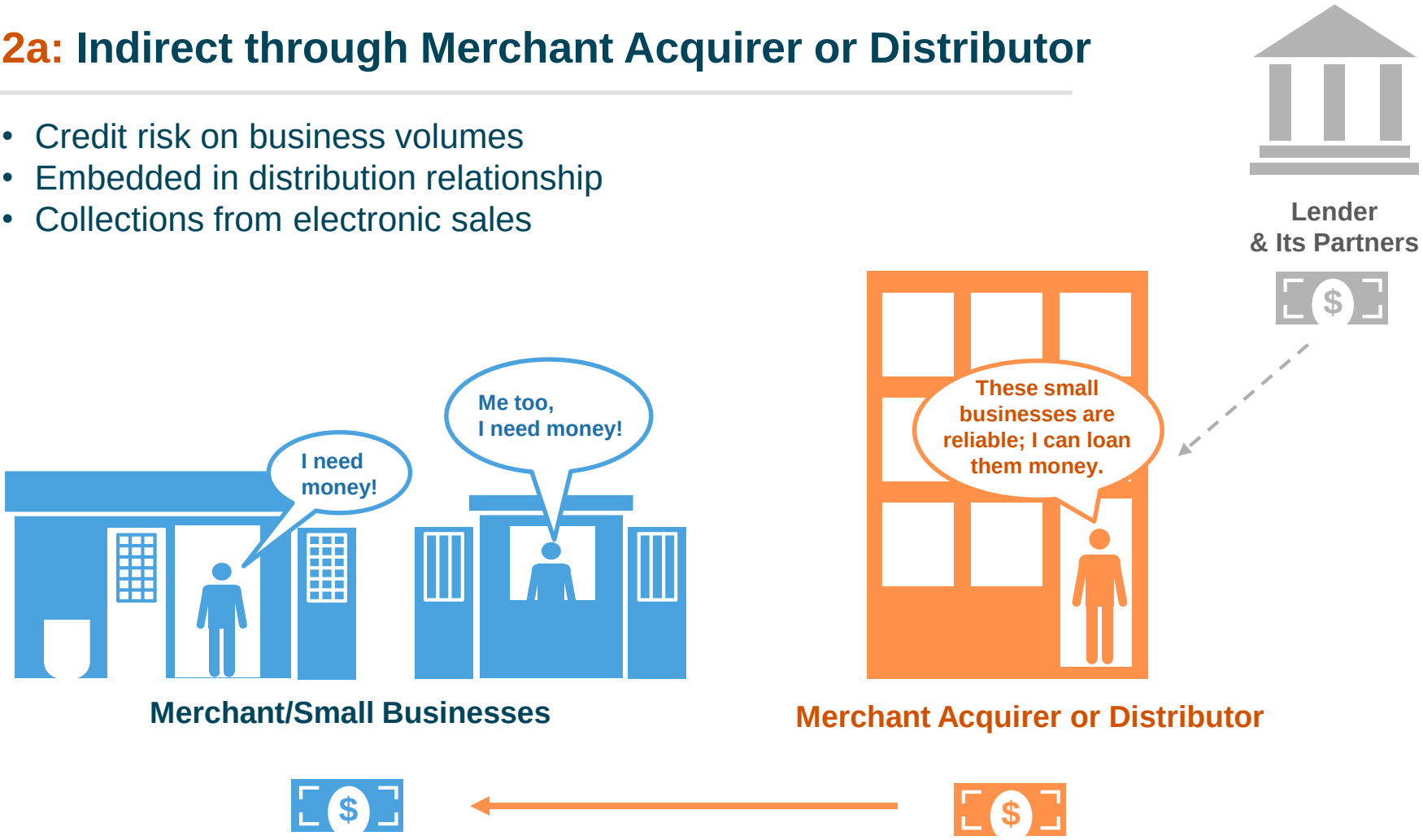
Individual
… who may also run a small business or farm.

Lender
& Its Partners

Variety of Digital Credit Approaches

2a: Indirect through Merchant Acquirer or Distributor

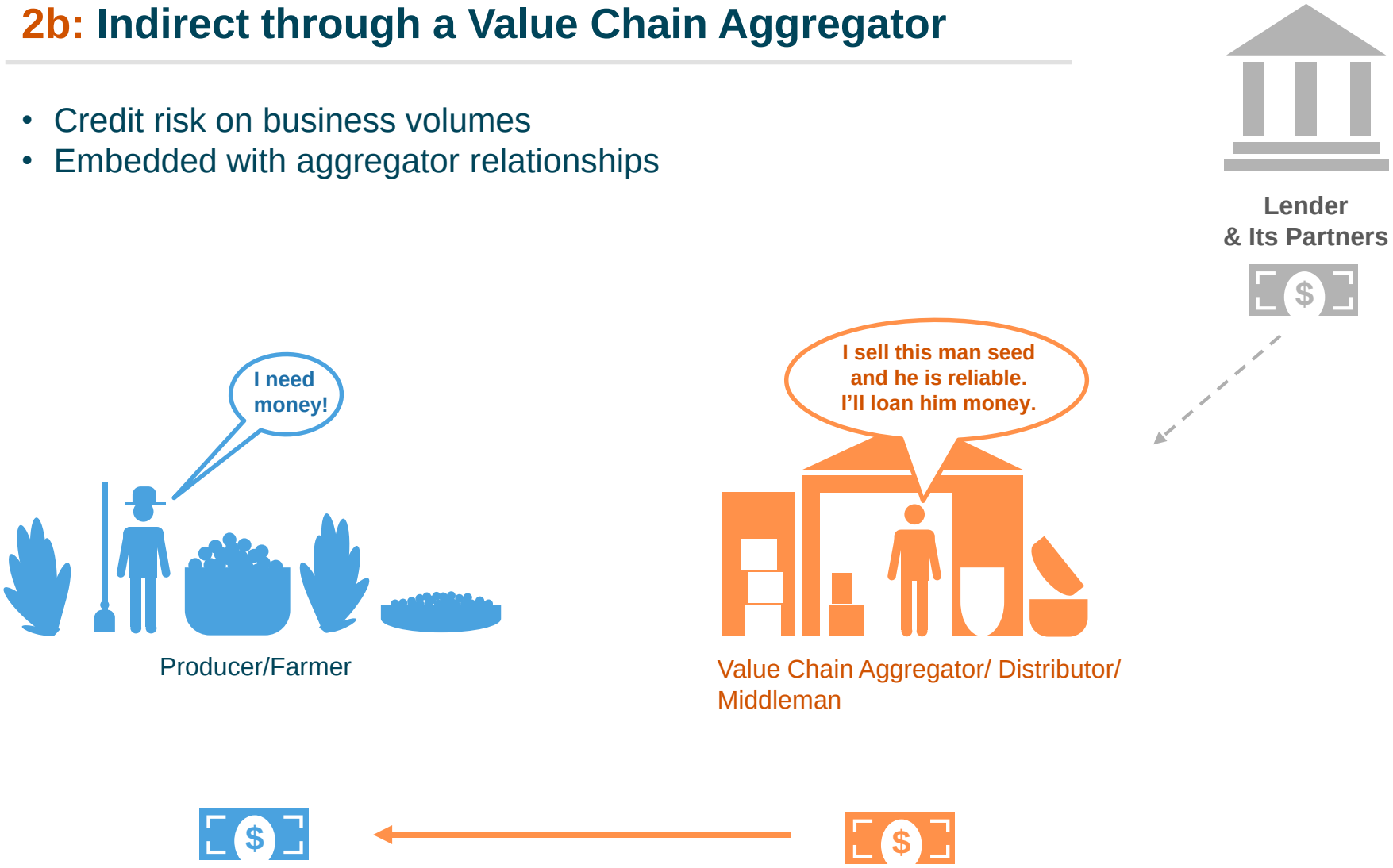
- Credit risk on business volumes
- Embedded in distribution relationship
- Collections from electronic sales



Variety of Digital Credit Approaches

2b: Indirect through a Value Chain Aggregator

- Credit risk on business volumes
- Embedded with aggregator relationships



Variety of Digital Credit Approaches

1. Direct to Individual

For example:

- M-Shwari (Kenya, 2012)
- EcoCashLoan (Zimbabwe, 2012)
- M-Pawa (Tanzania, 2014)
- Timiza (Tanzania, 2014)
- Mjara (Ghana, 2014)
- Eazzy Loan (Kenya, 2015)
- KCB M-PESA (Kenya, 2015)
- Instaloan (Philippines, 2016)

2a. Indirect via Merchant Acquirer / Distributor

For example:

- Kopo Kopo (Kenya, 2012)
- Konfío (Mexico, 2013)
- Tienda Pago (Peru, 2013)

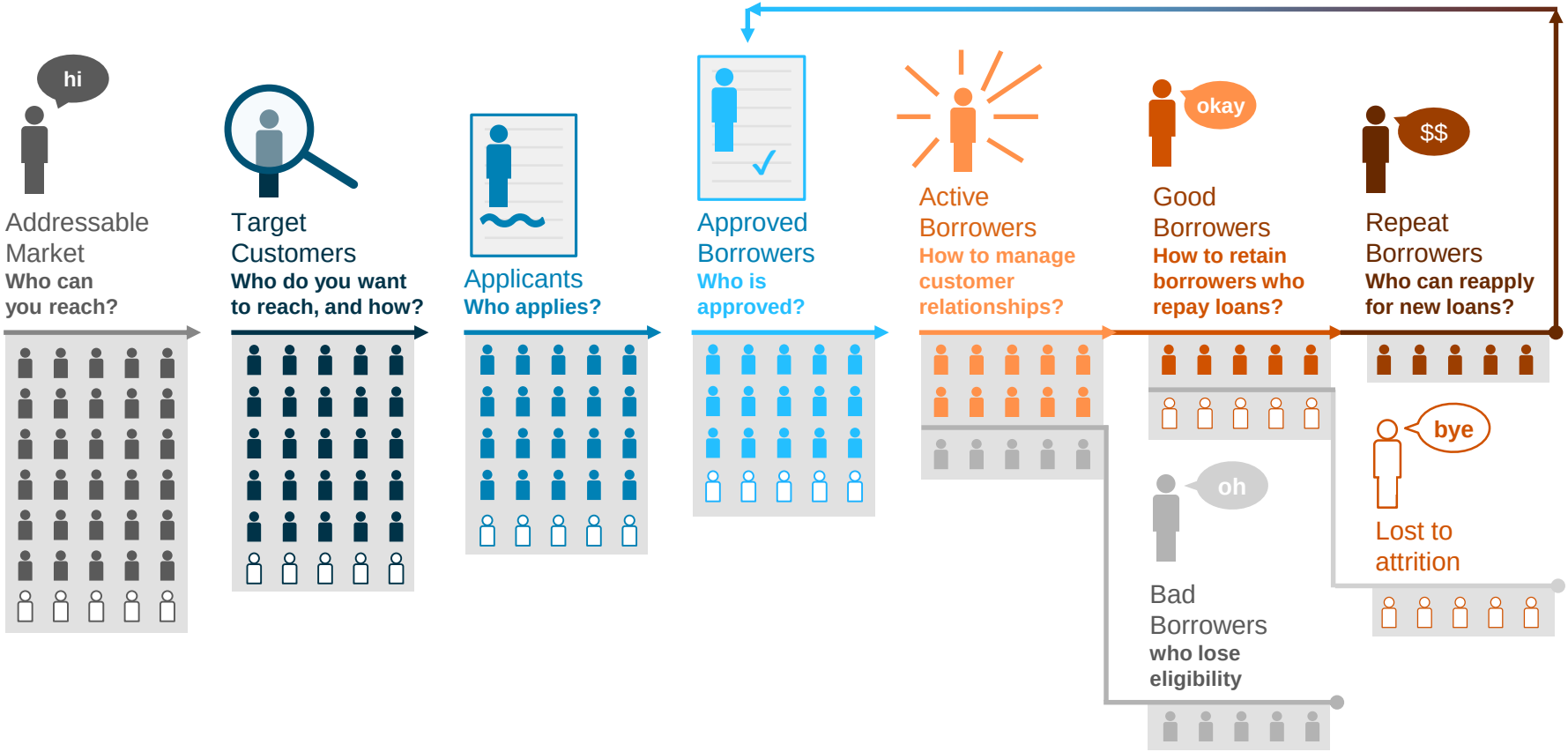
2b. Indirect via Value Chain Aggregator

- Several pilots in progress

How It Works: Framework

PHOTO CREDIT: Wu Shaoping, 2010 CGAP Photo Contest

How Does Digital Credit Work?



SOURCE: Jamal Rahal, CETA Technologies & Analytics (derived from a similar slide)

Example: Timiza

Providers	airtel, JUMO
Country/Launch	**Tanzania** (2014)

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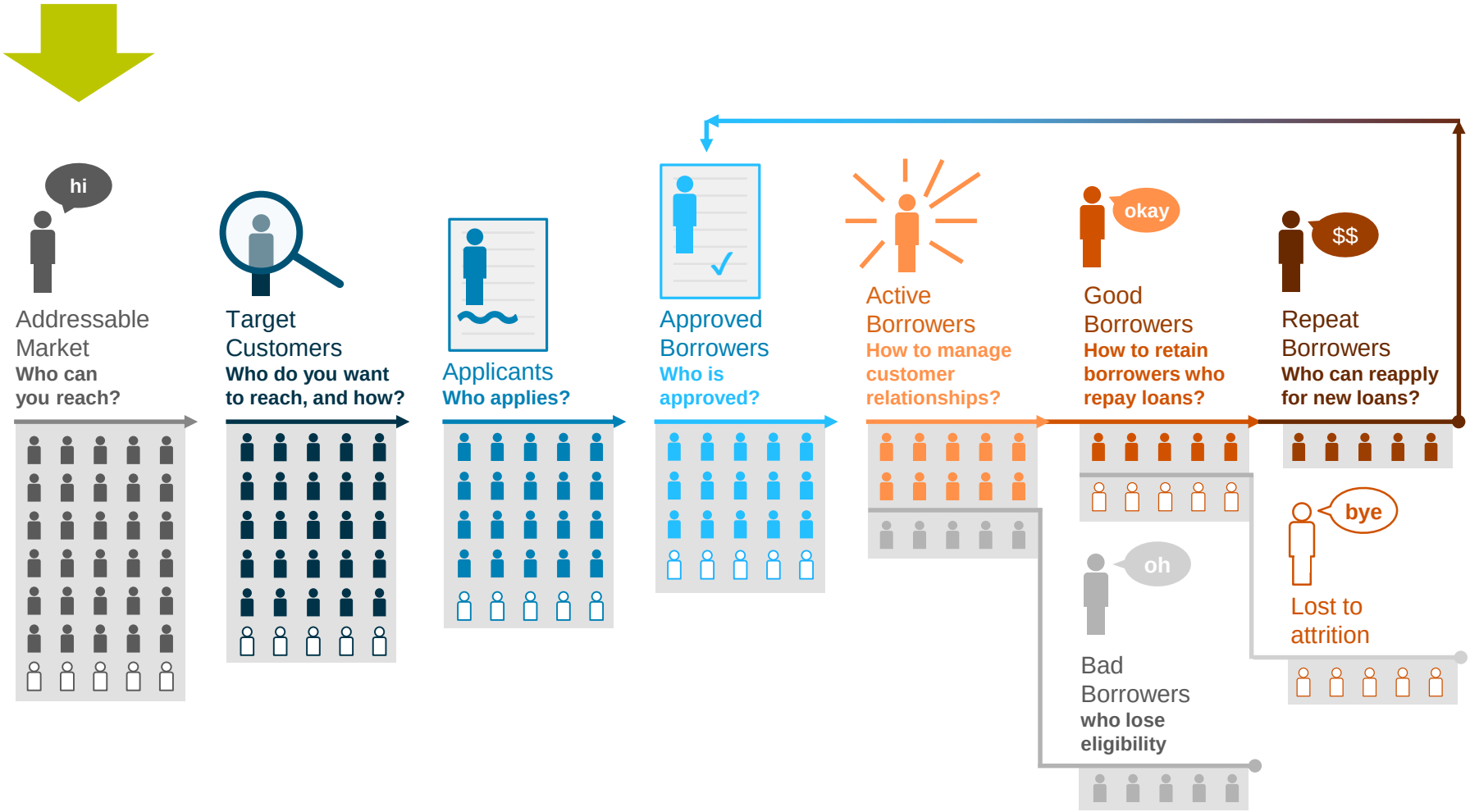
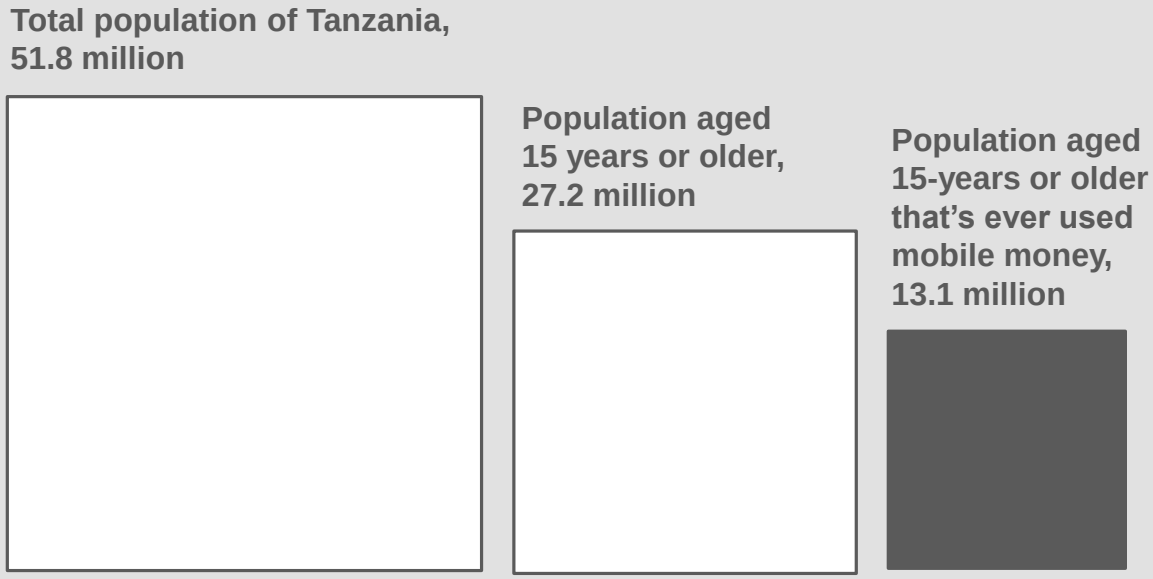


Example: How Digital Credit Works, Timiza

Addressable Market
Who can you reach?

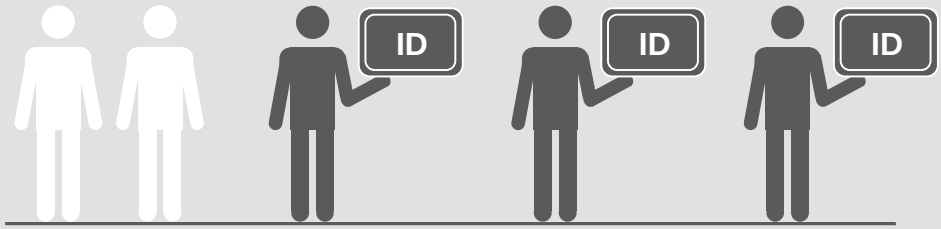
What does the addressable market in Tanzania look like?



Mobile Money Provider Share

Vodacom M-PESA	38%
Tigo Pesa	33%
Airtel Money	**27%**
Zantel Ezy Pesa	2%

Only 3 in 5 adults meet ID requirements for account registration.
Source: InterMedia Tanzania FII Tracker survey, 2014



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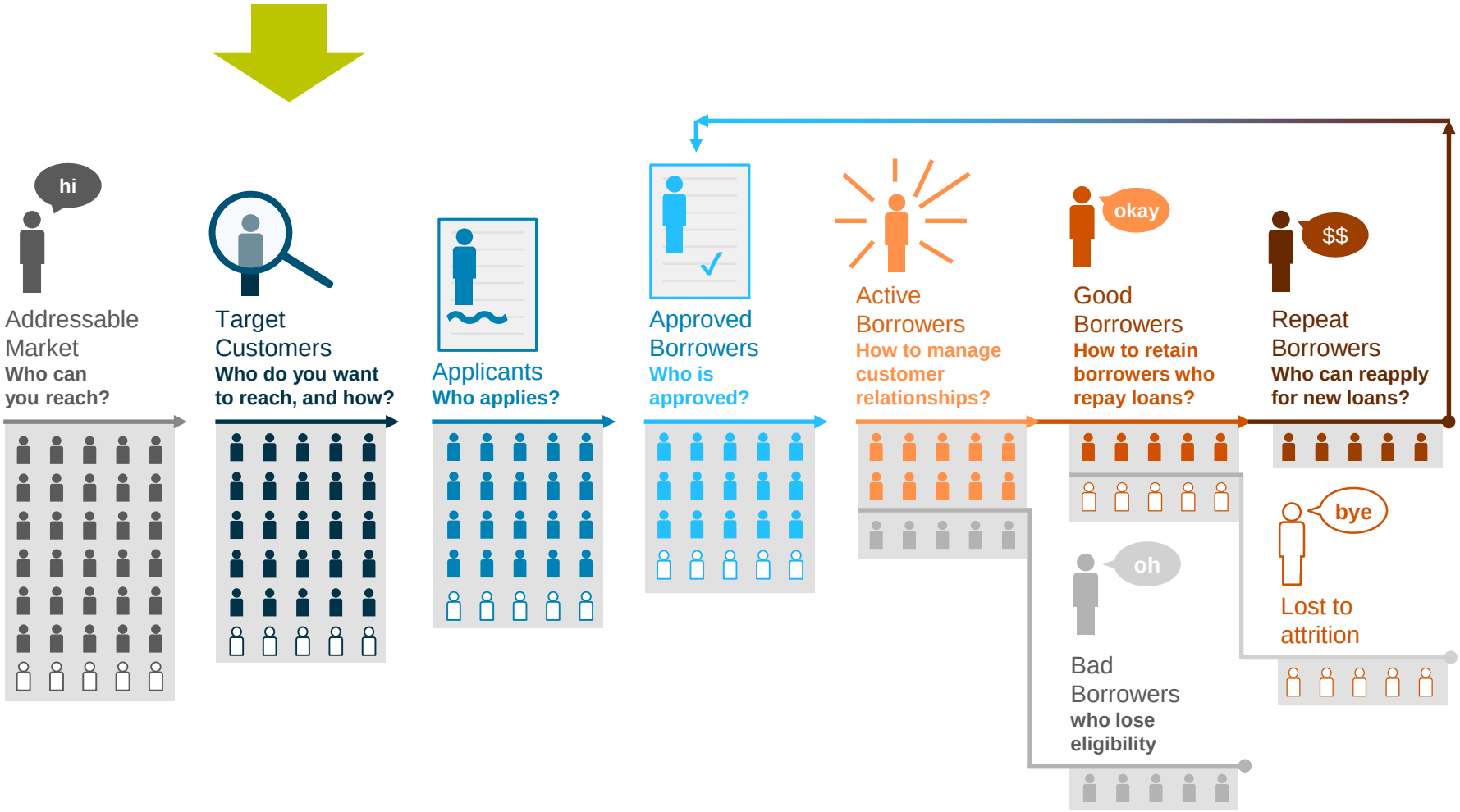


Example: How Digital Credit Works, Timiza

Target
Customers
Who do you want to reach, and how?

Based on your understanding of the addressable market, a series of considerations will shape your marketing and service design.

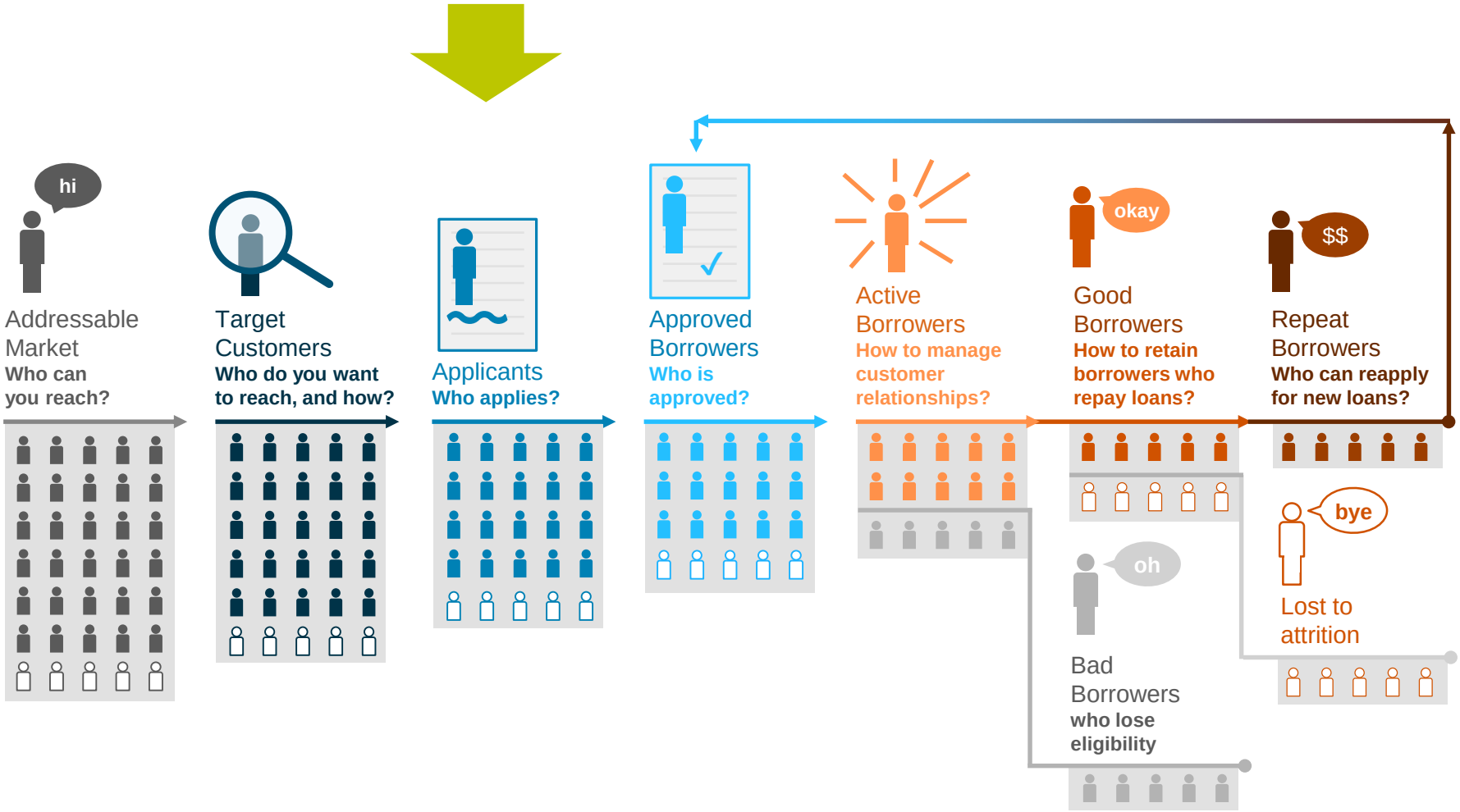
Airtel customers and new customers in need of short term liquidity

- “Quick easy cash”
- A term of one, two, three, or four weeks
- A loan size of USD10

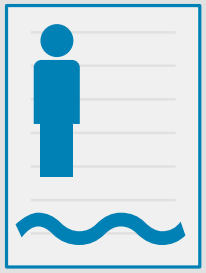
- Market share for Airtel voice and Airtel Money
- Diversify revenue

- Market research and three months pilot
- SMS blasts
- TV, radio, and billboard ads
- Example

How Does Digital Credit Work?



Example: How Digital Credit Works, Timiza



Applicants
Who applies?

In order to be eligible for a Timiza loan, applicants must fulfill certain criteria tied to, for example, age, airtime and mobile money subscription tenure, and previous payment history.

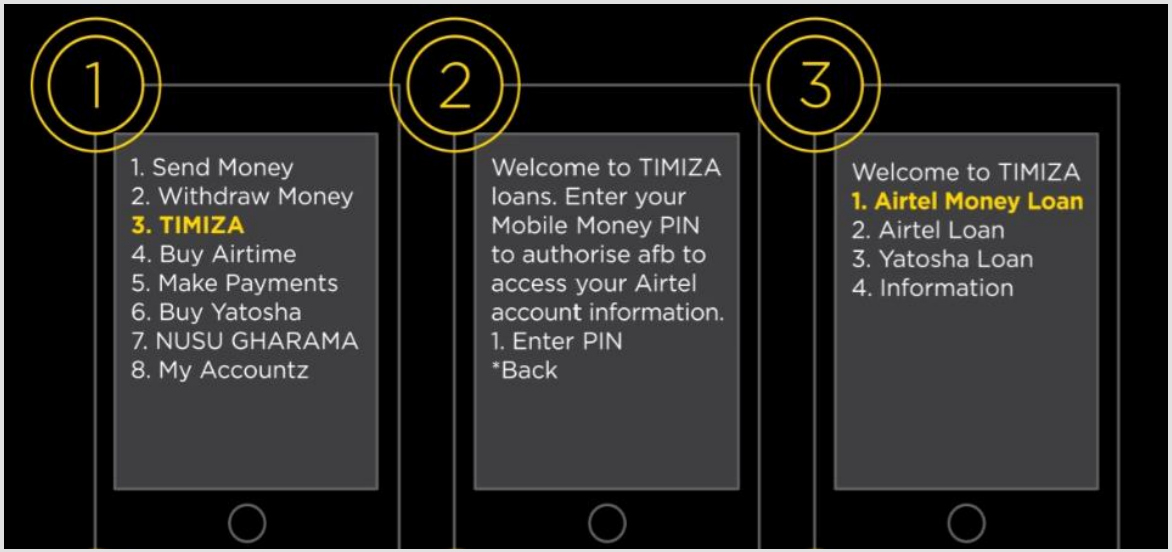
Loan Eligibility Criteria:

- Age 18 or older
- Airtel Customer for 90 or more days
- Active Airtel Money Account
- No outstanding loan or negative behavior with Jumo at time of application

Scoring Model:

- Customer demographic data (e.g. age, gender)
- Subscription tenure
- GSM data and MM data

Application Process:



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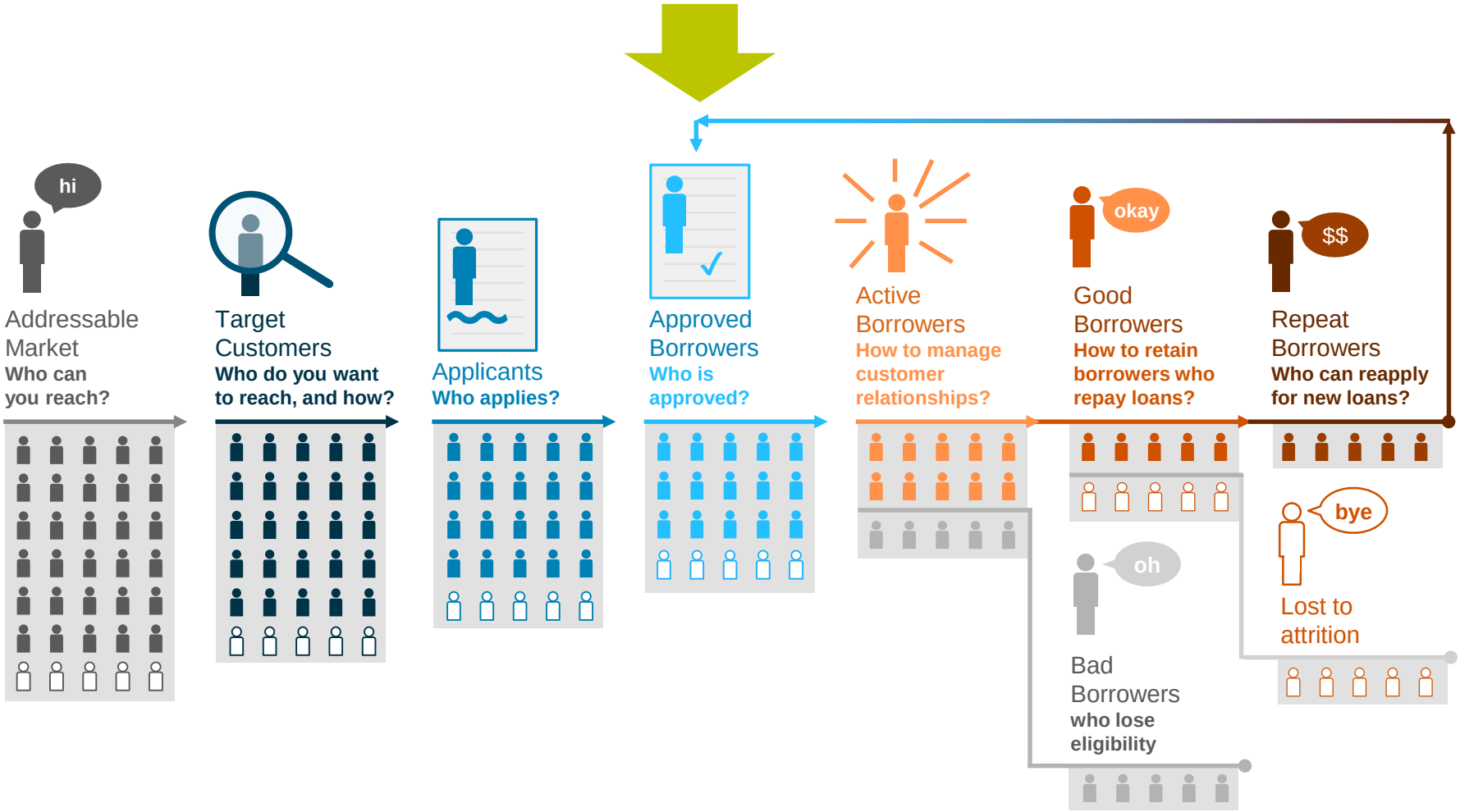
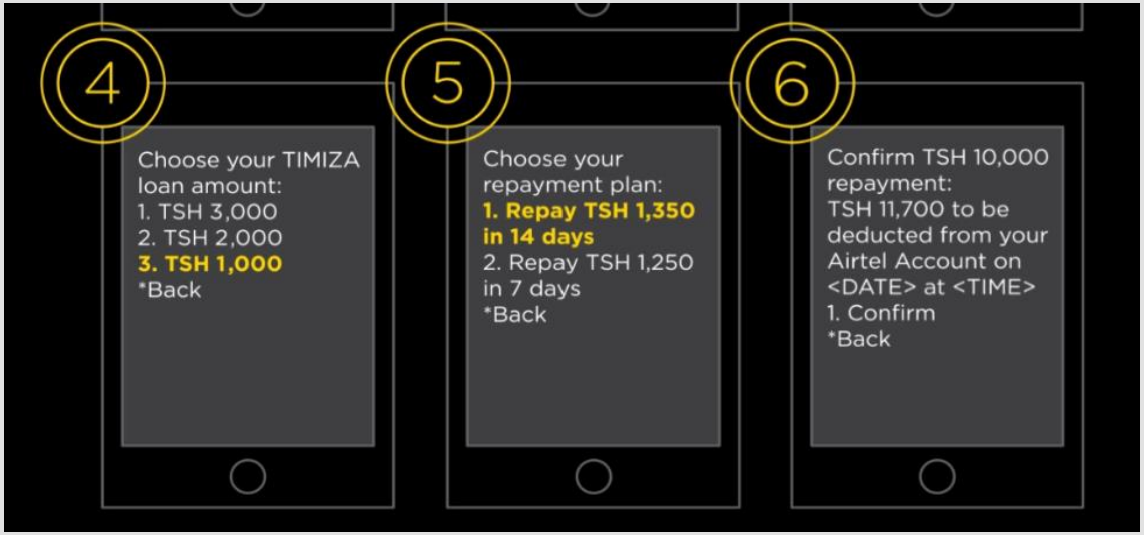


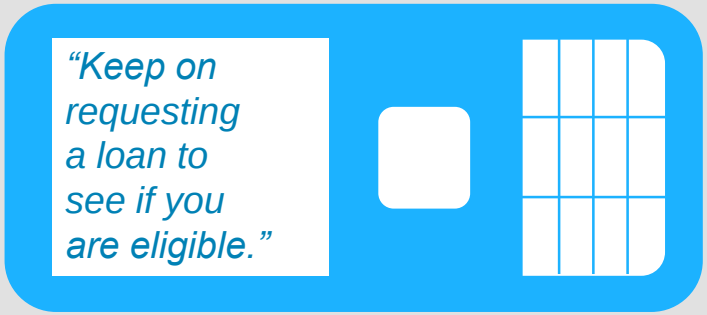
Example: How Digital Credit Works, Timiza

Approved Borrowers
Who is approved?

If Accepted: Loan Limit and Repayment Plan



If Rejected:



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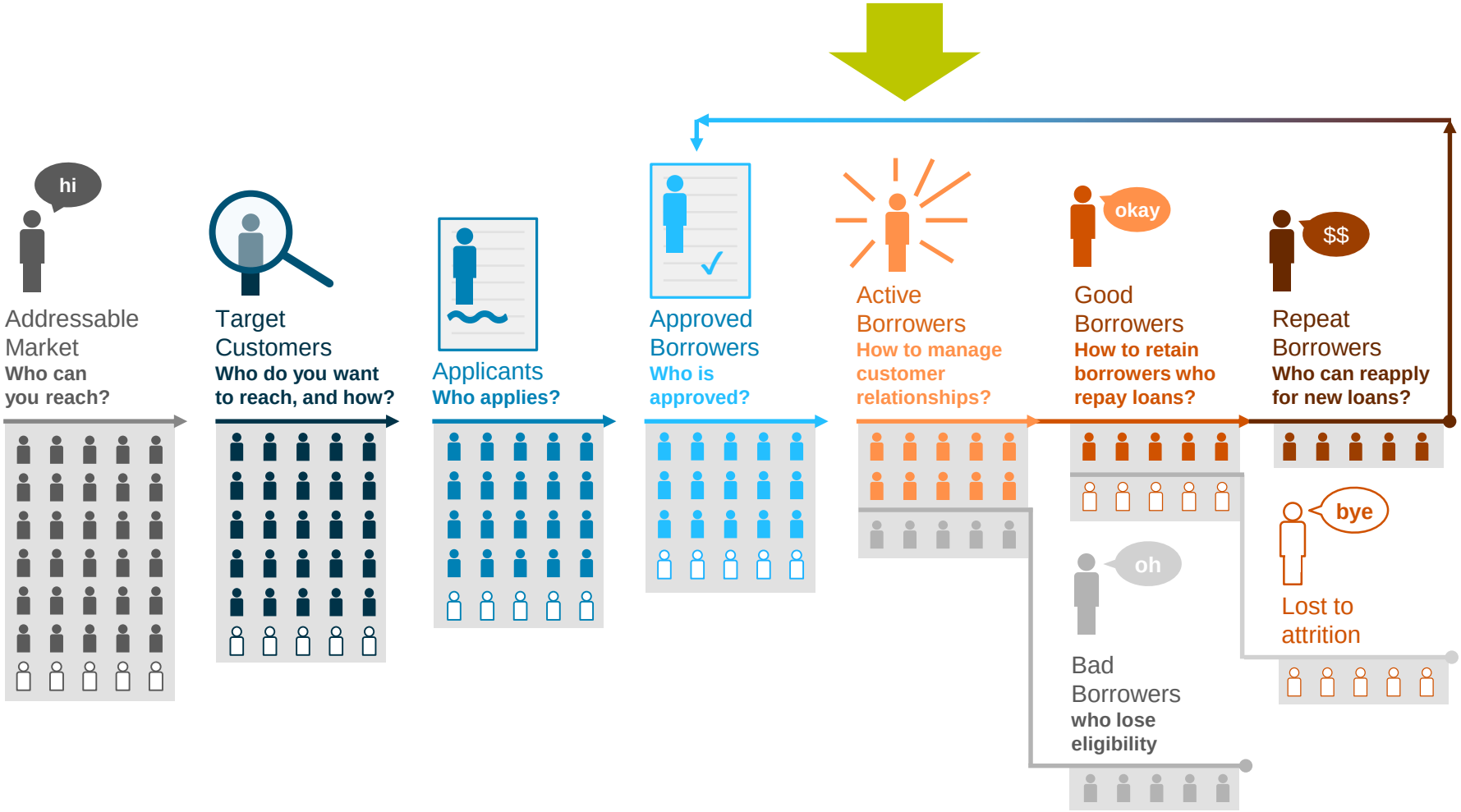
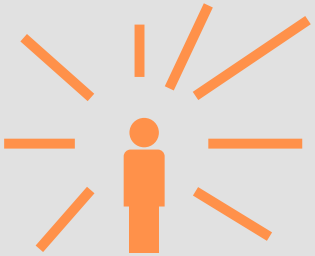


Example: How Digital Credit Works, Timiza



Active Borrowers
How to manage customer relationships

Customer Queries

- Airtel Customer Call Center
- Airtel Facebook page

Customer Relationship Management (CRM) System
Home-built (Jumo) Customer Management System

How to hold onto the "good" borrowers

- SMS messages
- Higher loan limits

How to deal with "bad" borrowers

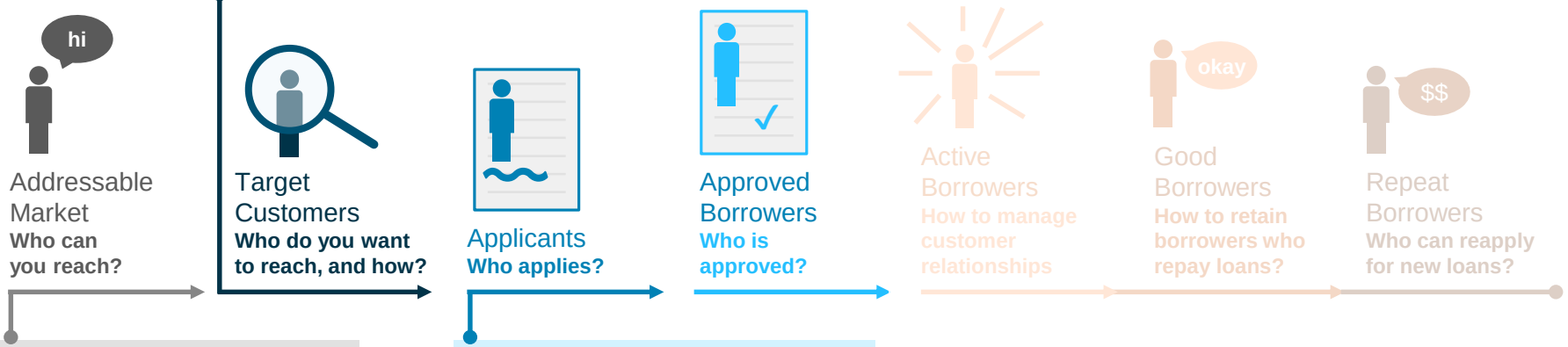
- One off fine of 10% of loan value
- SMS and call reminders
- NO cutting of phone line

Learnings

PHOTO CREDIT: Ariel Slaton, 2012 CGAP Photo Contest

Examples of Mistakes and Learnings

Poor Targeting
One telco in East Africa ran an acquisition campaign offering digital credit for free; attracting a high risk pool of applicants. Credit scoring could not overcome this adverse selection.

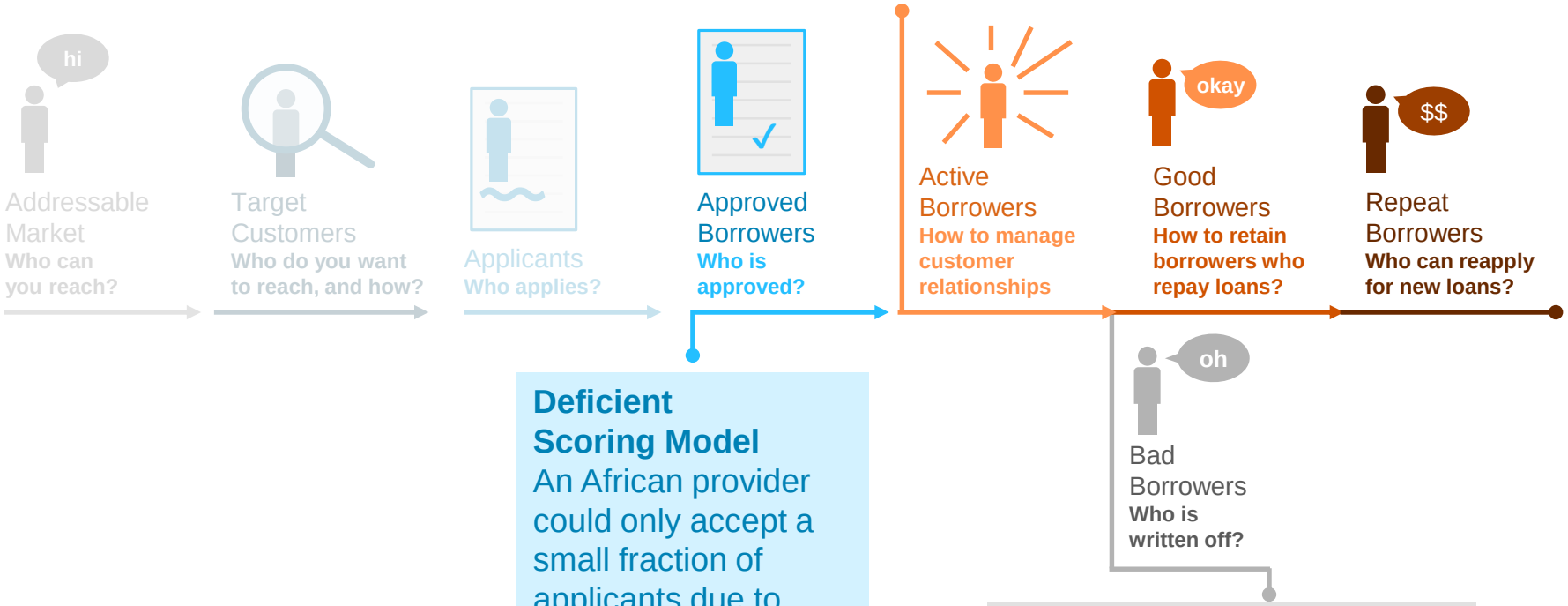


Infrastructure Challenges
Absence of a reliable national ID makes replicating M-Shwari in Tanzania more difficult; hard to link user of SIM account owner.

Cumbersome Application Process
A loan product in West Africa requires three consecutive monthly installments before the first loan, making the service hard to sell to new customers.

Examples of Mistakes and Learnings

Poor Product Design and Pricing Decisions: One provider charged a **transaction fee** to move funds between their mobile wallet and bank account, making the service unviable.



Deficient Scoring Model
An African provider could only accept a small fraction of applicants due to **weak data available and poor credit scoring**.

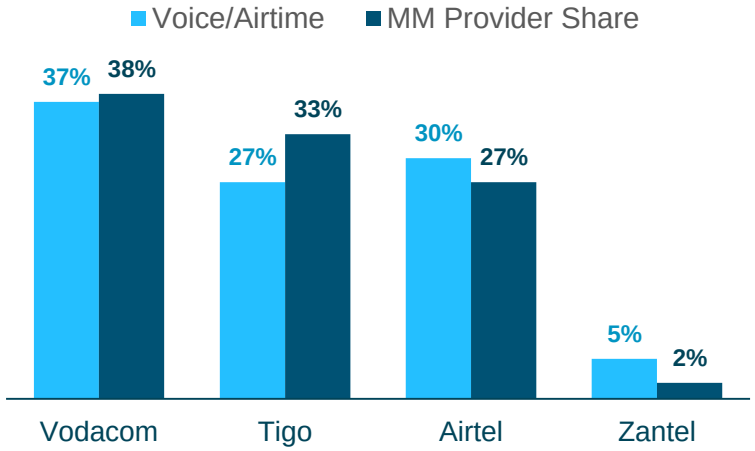
Lack of Collections Strategy
Many deployments focus on credit scoring and neglect **collections and follow-up**. Backstopping is as important as initial scoring.

Stay Away or Invest?

PHOTO CREDIT: Uptal Das, 2014 CGAP Photo Contest

Strategy: Market and Institution Specific

TANZANIA



Timiza

Airtel
- Increase market share
- Diversify revenue

Jumo
- Market entry

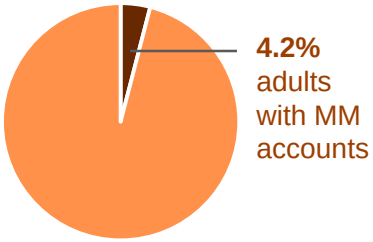
Preliminary results
- 300% churn reduction
- Significant increase in active MM users

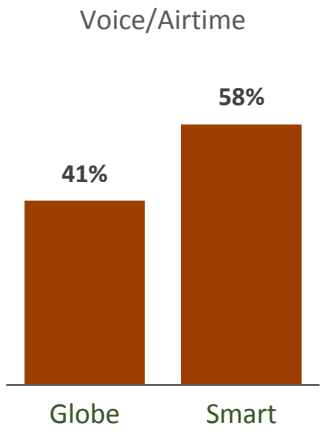
M-Pawa

Vodacom
- Defend voice and mobile money
- Diversify revenue

CBA
- New asset category
- Customer acquisition

PHILIPPINES





Instaloan

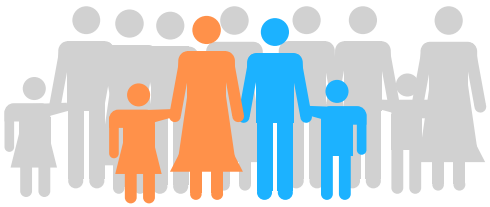
Globe
- Acquire MM accounts
- Increase voice

Mynt
- Grow loan portfolio
- Grow customer base (from informal lenders)

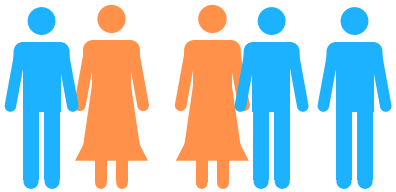
Strategy: Is It Right for You?

Country context

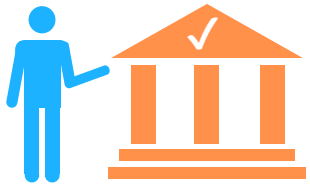
Population



Population age 15 and older



Financially included



Mobile phones

Mobile money accounts

Cash in/out

Internet users

Sound Credit Bureau

Reliable National ID

Introduction: Summary Points

- Pure digital credit is **instant, automated** and **remote**;
- Two broad approaches to digital credit delivery: (1) direct to **individuals**, (2a) indirect via **merchant acquirers/distributors**, or (2b) indirect via **value chain aggregators**;
- There is a **common framework** for understanding how (direct to individual) digital credit delivery works;
- Is it **good strategy to invest in digital credit deployments?** Reasons vary by institution and context.

INTRODUCTION 3

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What is Credit Scoring?

PHOTO CREDIT: Chi Keung Wong, 2013 CGAP Photo Contest

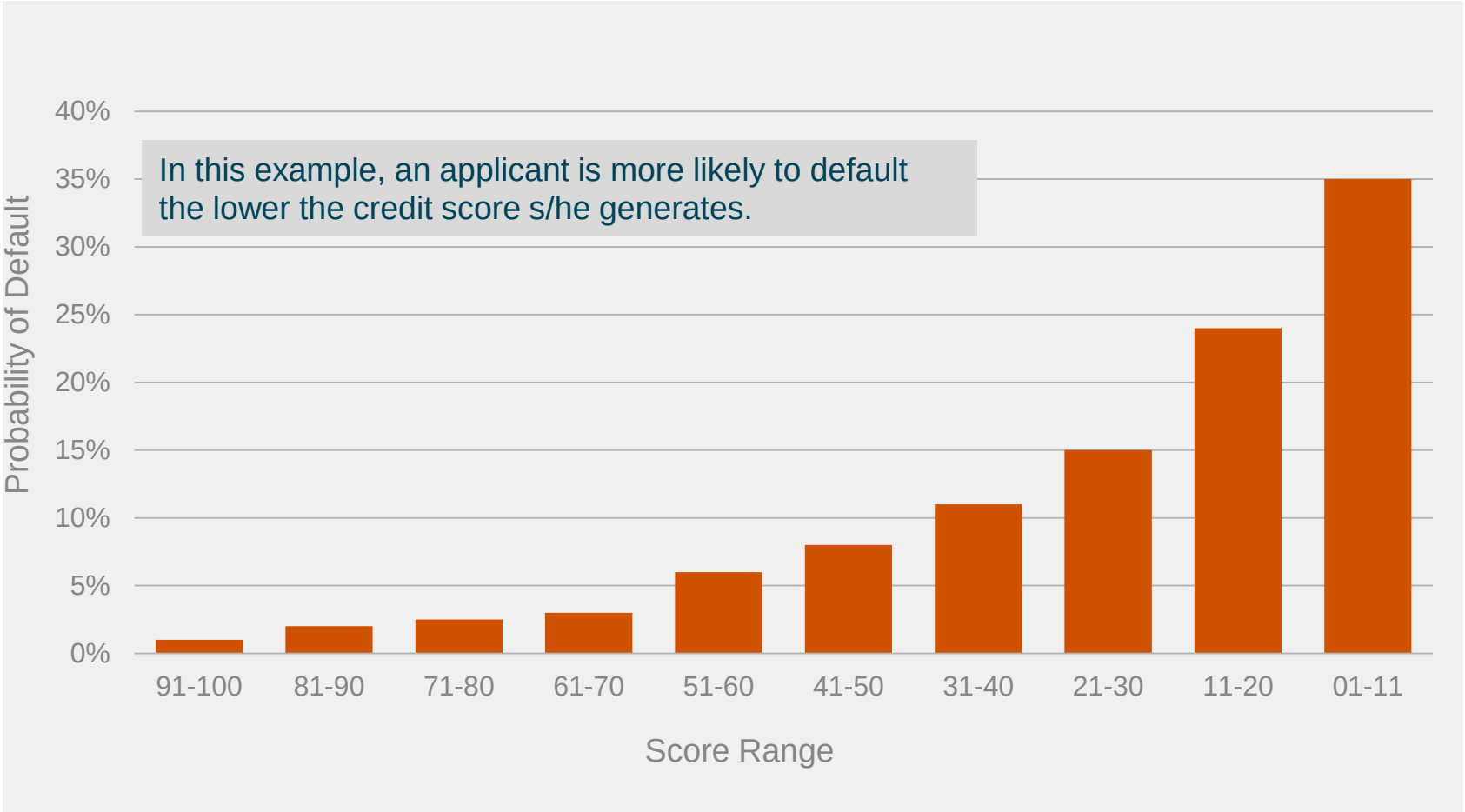
What is Credit Scoring?

Credit scoring is **one of several risk management tools** in digital credit delivery:

Origination	Credit Scoring	Customer Management	Collections

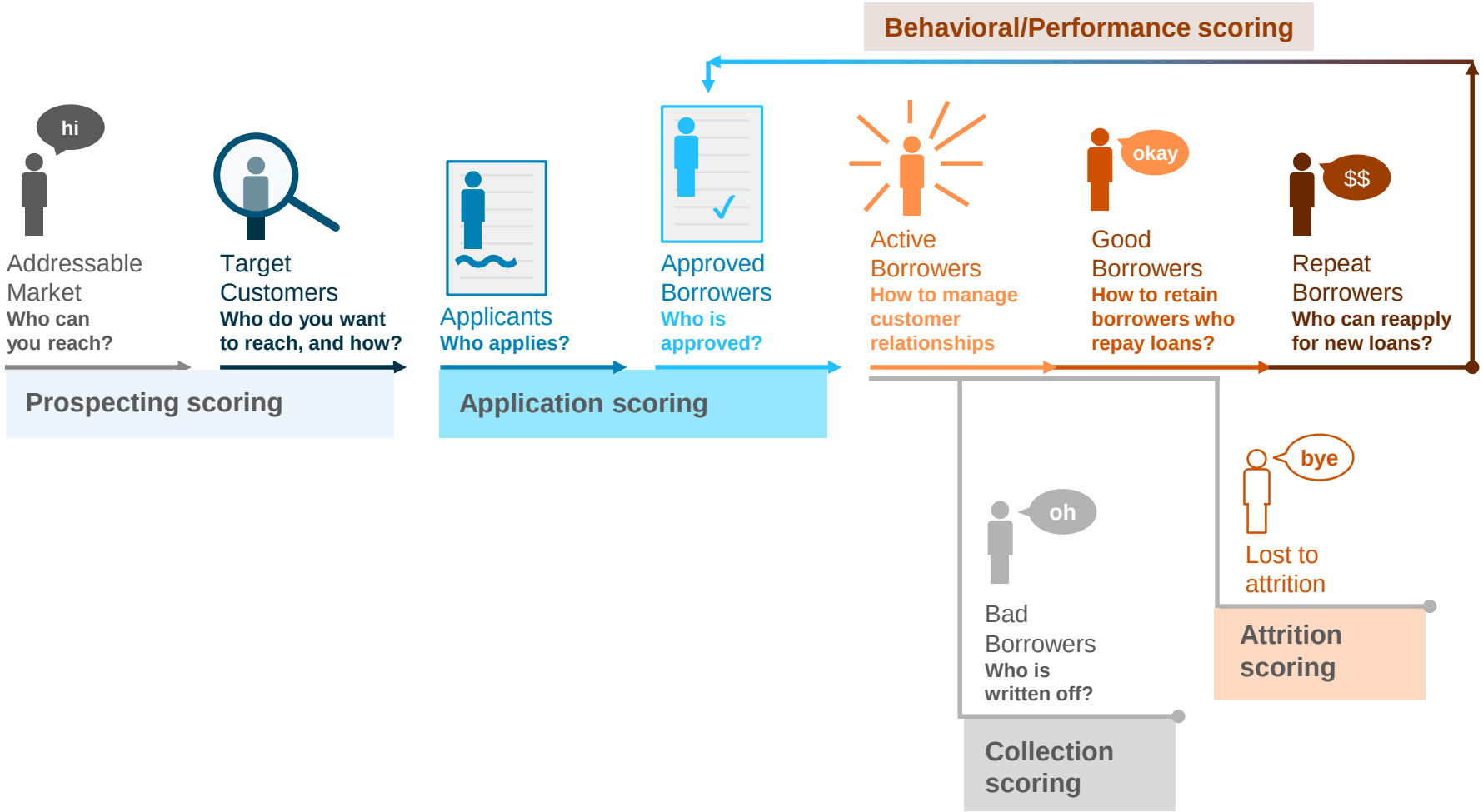
What is Credit Scoring?

It is an analytical tool that evaluates an applicant's **probability of default.** This tool uses **past data to predict future** probabilities of "good" or "bad" repayment behavior.



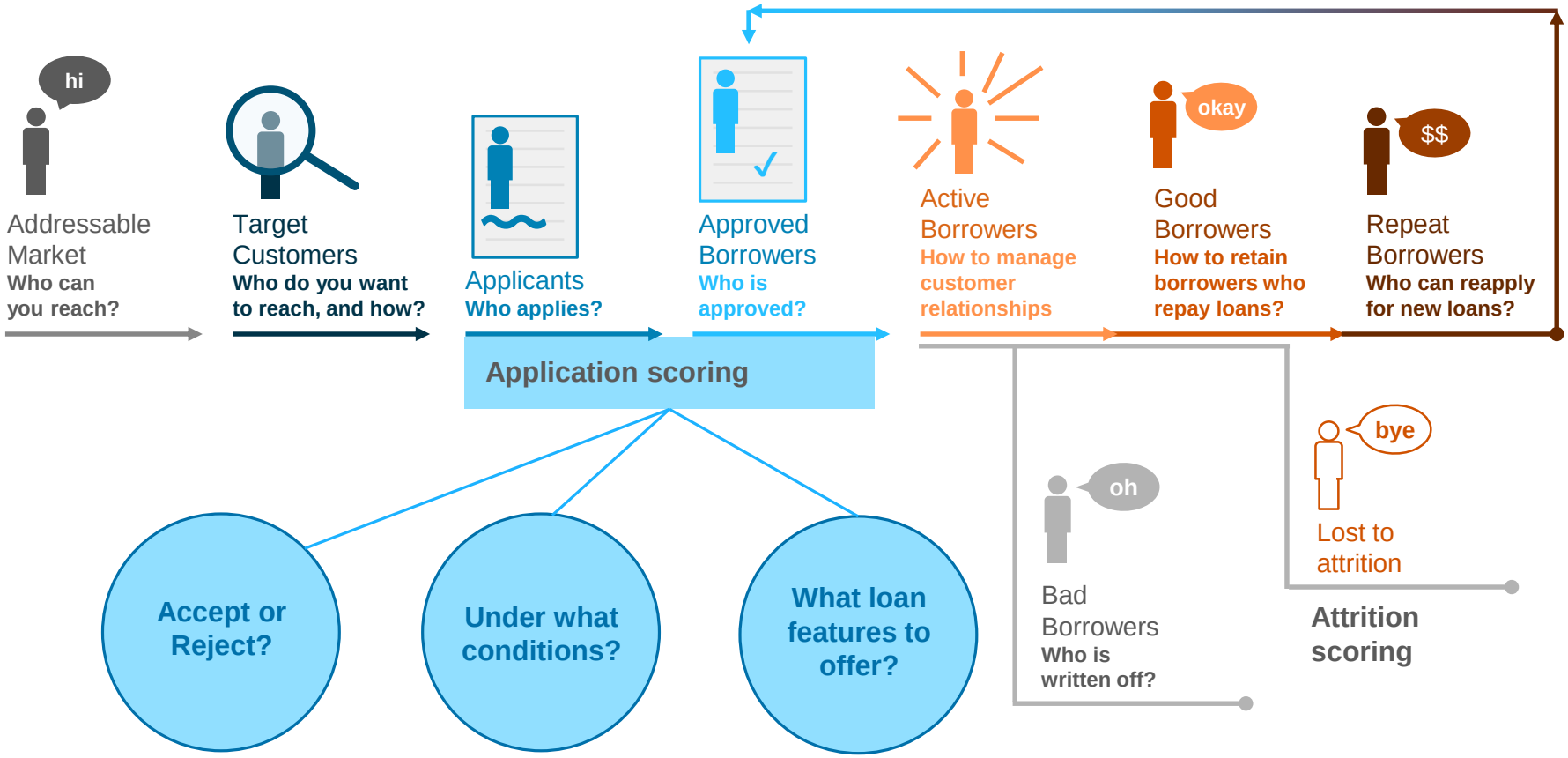
What is Credit Scoring?

Scoring happens **at various stages** of the credit delivery cycle. For each stage, a **different scoring model** with different sets of data variables is used.

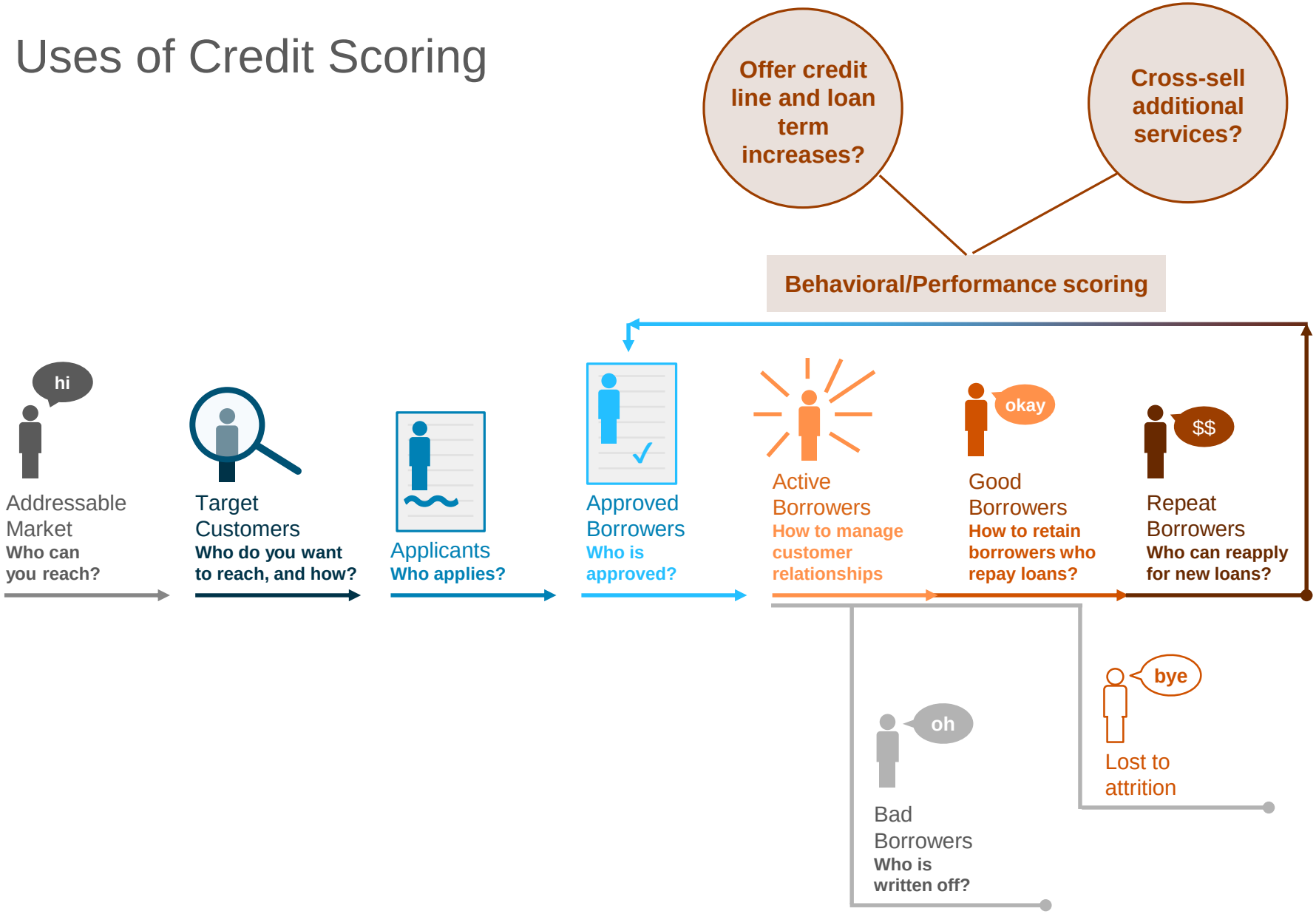


Uses of Credit Scoring

Credit scoring **informs various decisioning processes**, for example:



Uses of Credit Scoring



Benefits of Credit Scoring

Control and reduce your loan losses

- Minimize denials of creditworthy applicants, while keeping out high risk applicants

Improve accuracy of decision making

- Use of empirically derived mechanisms for objective and consistent decisioning
- Reduced space for human error

Manage risk at scale

- Reduced customer turnaround time
- Lower per-unit administrative costs

Relevance to digital finance

Allows for instant decision-making at scale…

- Reliance on automated risk management processes

… with limited in-person interactions

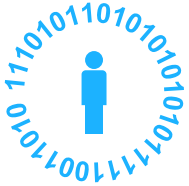
- Remote account opening and customer management.

How to Build a Scorecard?

PHOTO CREDIT: Kim Chog Keat, 2012 CGAP Photo Contest

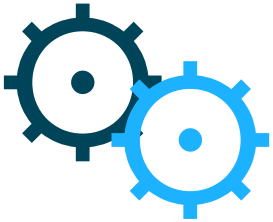
How to build a scorecard?

Providers face many considerations when developing a credit scoring solution, including:



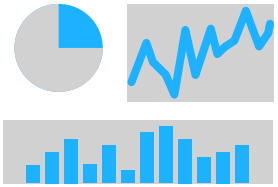
Data:

- What are your available data sources?



Expertise:

- Do you have capacity and expertise in-house and through a 3rd Party? Can you complement both approaches?



Methodology

- Which discriminants will predict probability of default?
- What are the cutoff scores for accepting good/bad borrowers?
- What are the relevant business considerations?

Data

The scorecard you use depends on the **data sample** you have available. Generally, there are two broad types of scorecards in digital credit:

Generic Scorecard
Developed from a large pool of data representative of the whole market (usually from credit bureau)

- Does not require in-house scoring expertise
- Cheaper than building own scorecard
- Relatively easy to implement

Drawback
Best with availability of a solid credit bureau. May not have predictive power.

Custom Scorecard
Custom-tailored model using internal data

- Higher accuracy
- More flexible, as adjustable over time

Drawbacks

- Requires good quality and reliable data
- Requires capacity and expertise to develop and maintain

In digital credit (low-income markets), most utilize custom scorecards

Expertise

Who has the capacity and skills to develop a scorecard?

Important considerations

- Developing a custom-tailored scorecard in-house requires significant resources (human and financial);
- Outsourcing may mean the lender has insufficient knowledge about the inner workings of the model (“black box” problem).
- Knowing the internal scorecard mechanisms are important for:
  - Customer communications: Explaining why an applicant is approved/rejected
  - Performance tracking and adjustments: Performing updates and tweaks over time
- Hence, a **blended approach** balancing your internal resources and external 3rd Party expertise may do well.

Methodology

1. **Assess the data available**
   - You will always start with a sample dataset to develop your scorecard.

2. **Define "good" and "bad" borrowers around your business objectives**
   - What are the business needs to strategically define "goods" and "bads"
   - Some common choices:
     - "Bad" borrowers: e.g. 90+ days past payment due date;
     - "Good" borrowers: e.g. Never delinquent, No claims, Never bankrupt, No fraud, Profitable.
   - Setting thresholds for "good" and "bad" is a business decision and will determine your scale and risk profile in the future.

3. **Identify and weigh discriminants according to their predictive power**
   - Statistically test variables that can help to discriminate between good and bad borrowers.

4. **Compile variables into a scorecard**
   - The result will be a formula or algorithm that uses some variables as input and calculates a probability of default (probability of turning "bad").

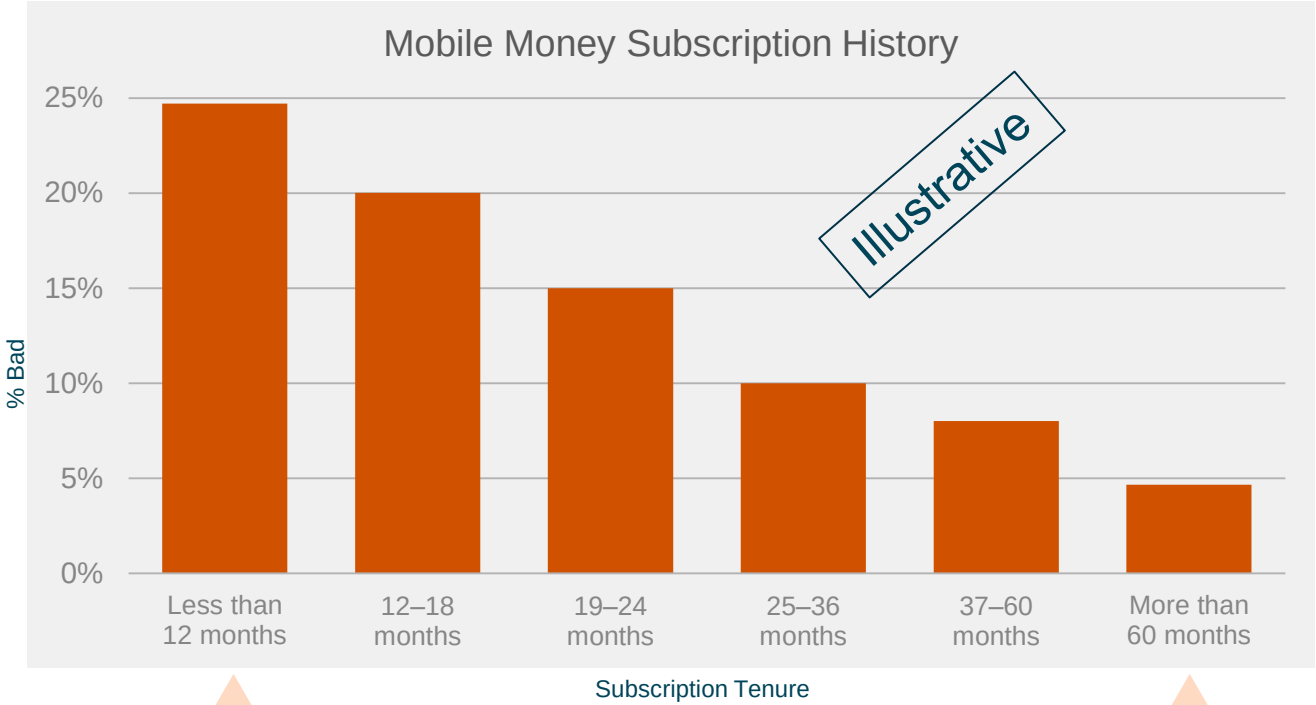
Note that lenders may base their initial lending decisions on customers meeting certain *eligibility criteria and rules*, rather than using a scoring model with cutoff points. During early stages of operation, lenders may also choose to accept more "bads" to further refine their algorithm.
Once a solid scoring model has been developed, new (first-time) applicants will be evaluated based on the characteristics and attributes that have been identified as predictive for good/bad borrowers (e.g. under the assumption that new applicants will behave similarly to previous borrowers).

5. **Test your scoring system and adjust over time.**

METHODOLOGY

Identify Discriminants

For example



In this example, we find that borrowers who have subscribed to a mobile money service for **less than 12 months are more likely to be "bad" borrowers** (24.7%) than those who have been on file for over 60 months (4.7%).

Other predictive indicators may include:

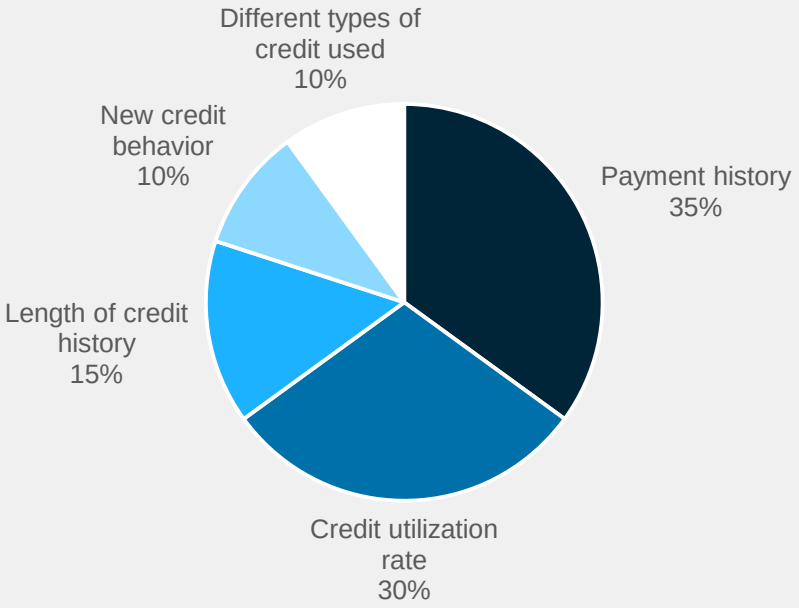
- Age
- Residence (own, rent)
- Number of years at residence
- Occupation
- Telephone
- Income
- Years on job
- Prior job
- Years on prior job
- Number of dependents
- Credit history
- Banking account
- Credit outstanding
- Debt/Burden
- Purpose of loan
- Type of loan
- Etc.

METHODOLOGY

Weigh Discriminants

For example

FICO Scorecard*



A FICO scorecard comprises a set of indicators, **weighing each in proportion to their predictive power.**

*FICO is one of the world's largest providers of generic scoring models. Note, however, that such a scorecard requires solid credit bureau data.

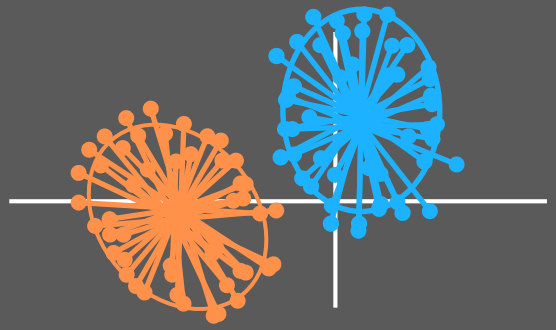
METHODOLOGY

Identify and Test Predictive Indicators

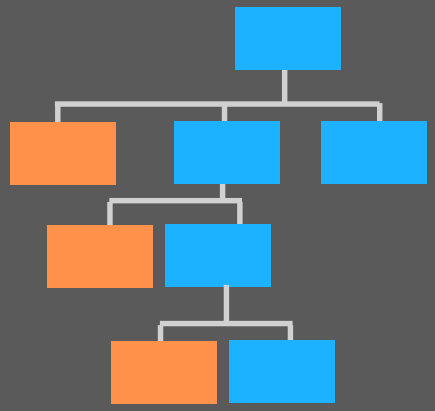
Most scorecards are built using proven methodologies, such as:

LOGISTIC REGRESSION

DISCRIMINANT ANALYSIS

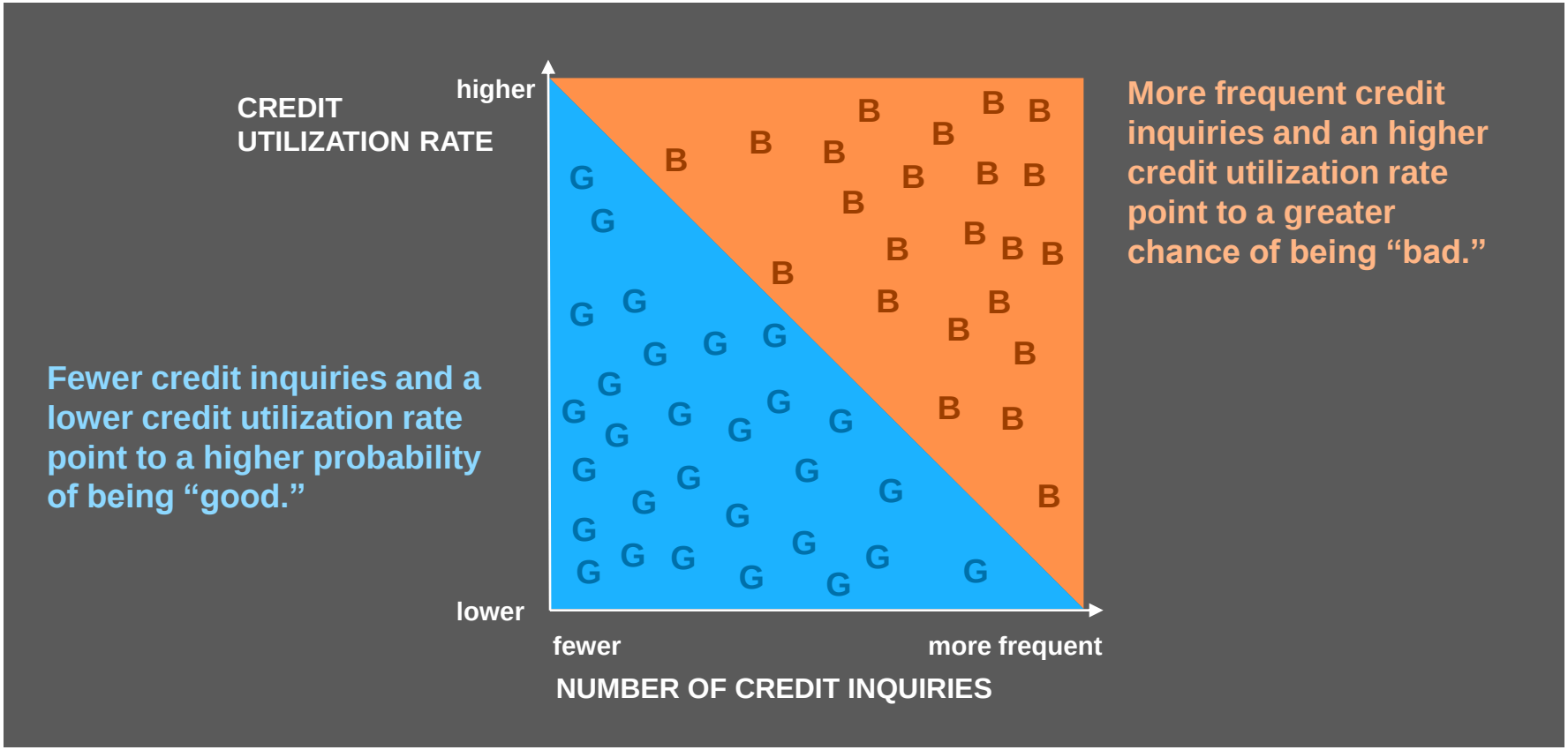


DECISION TREES



Logistic regression

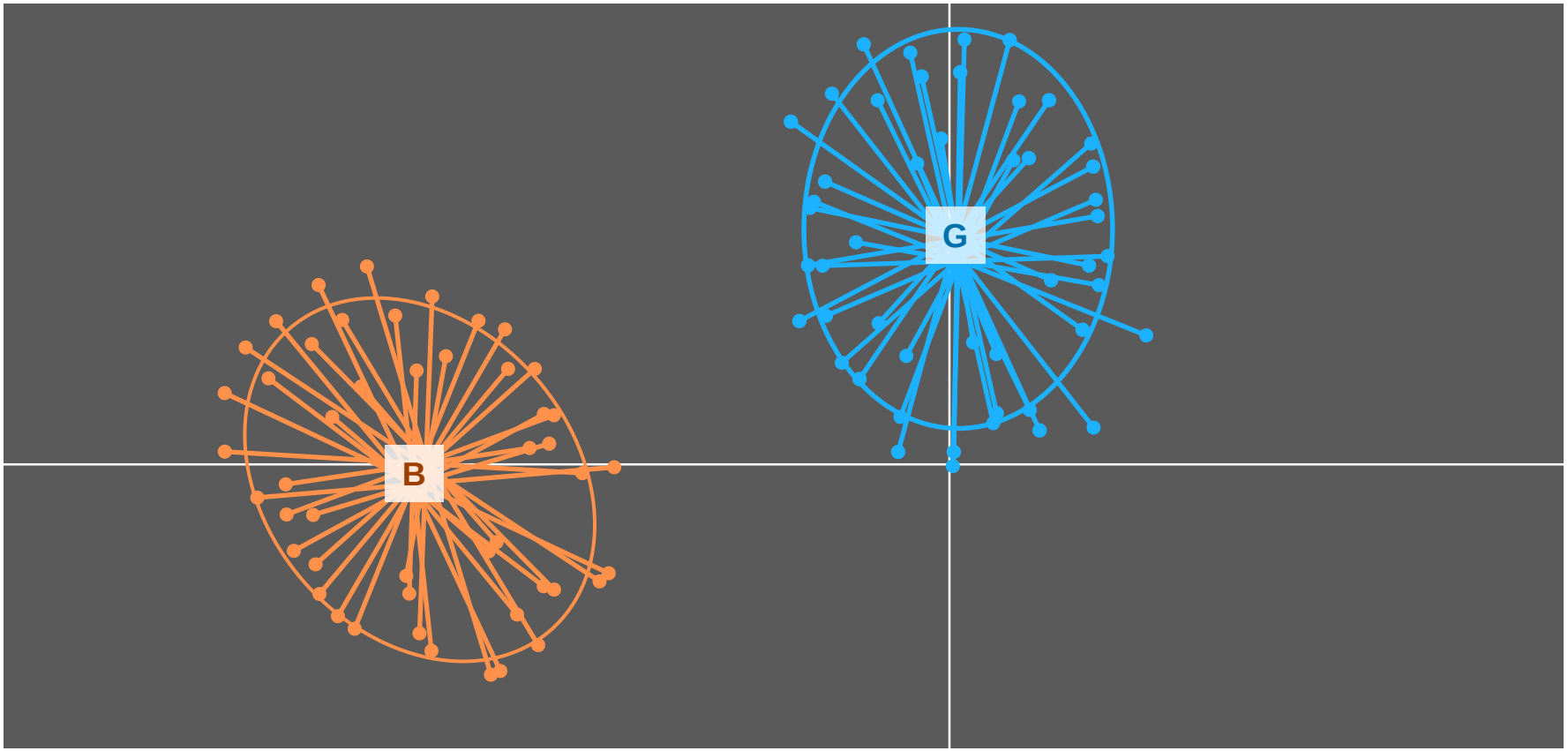
The regression is a classification algorithm, and the output of a binary logistic regression is a probability of class membership, in this case good or bad. Here an example using just two variables.*



*Usually the higher the credit utilization rate and the number of inquiries negatively affects the probability of being Good.

Discriminant analysis

Discriminant analysis classifies individuals by minimizing the differences within classes (either goods or bads), and at the same time maximizing the differences between classes (goods vs. bads). The output is also a probability of class membership.



Classification trees

Classification Trees help you better identify groups, discover relationships between them and predict future events based on target variables.

They make it easier to understand the relationship between variables and how they classify goods and bads.

Credit Rating

NODE 0

Category	%	n
Bad	41%	1,020
Good	**59%**	**1,444**
Total	100%	2,464

Income level

<=Low

NODE 1

Category	%	n
Bad	**82%**	**454**
Good	18%	99
Total	22%	553

Low, Medium

NODE 2

Category	%	n
Bad	42%	476
Good	**58%**	**658**
Total	46%	1134

>Medium

NODE 3

Category	%	n
Bad	12%	90
Good	**88%**	**687**
Total	31%	777

Number of credit cards

5 or more

NODE 4

Category	%	n
Bad	**57%**	**422**
Good	43%	322
Total	30%	744

Less than 5

NODE 5

Category	%	n
Bad	14%	54
Good	**86%**	**336**
Total	16%	390

Number of credit cards

5 or more

NODE 6

Category	%	n
Bad	18%	80
Good	**82%**	**375**
Total	18%	455

Less than 5

NODE 7

Category	%	n
Bad	3%	10
Good	**97%**	**312**
Total	13%	322

Age

Younger than 28

NODE 8

Category	%	n
Bad	**81%**	**211**
Good	19%	50
Total	16%	261

Older than 28

NODE 9

Category	%	n
Bad	44%	211
Good	**56%**	**272**
Total	20%	483

METHODOLOGY

Sample Scorecard

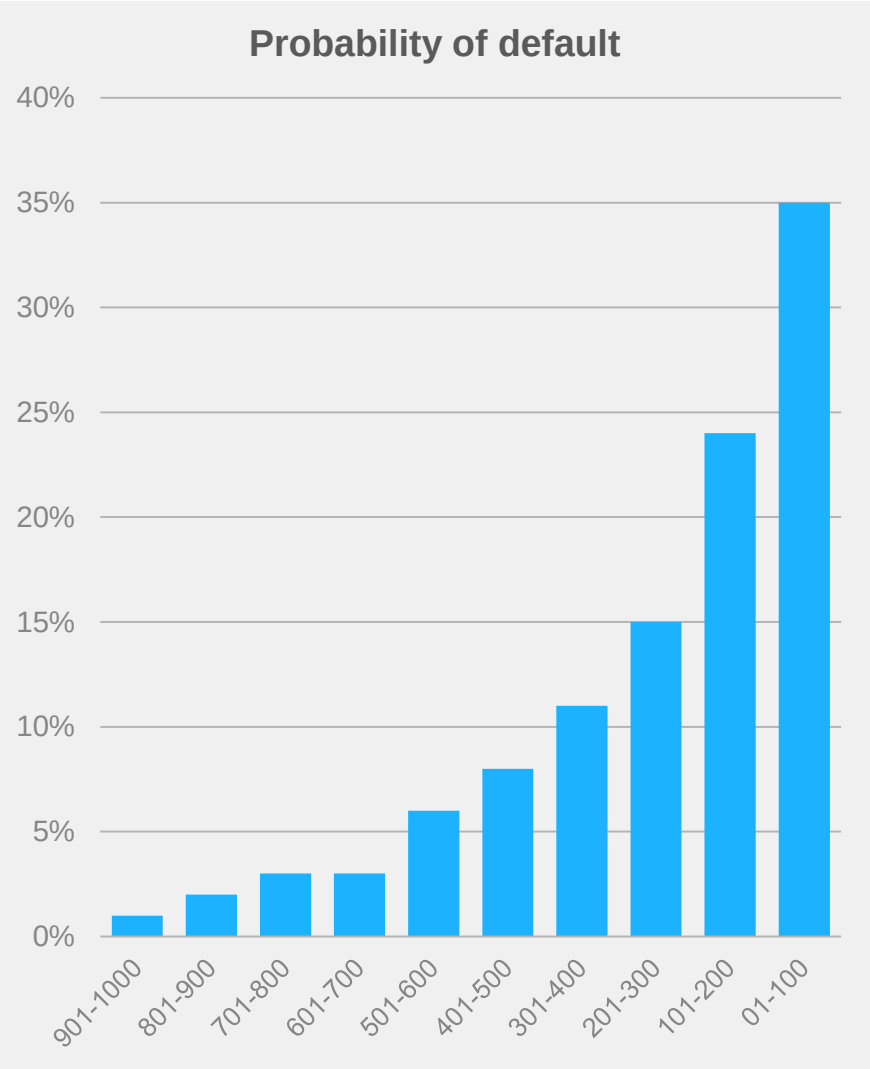


EXHIBIT 3-3
Sample Credit Scoring Table

Characteristics	*Assigned Classifications*	*Points*
Type of housing	Rents	0
	Lives with parents	15
	Owns	38
Age of applicant	18–20 years	0
	21–24 years	4
	25–55 years	27
	56 years or older	53
Household income	Unknown	22
	Less than $25M	0
	$25M–$40M	7
	>$40M–$60M	31
	>$60M–$75M	43
	Above $75M	61
Number of recent inquiries	0	66
	1–3	48
	4 or more	0
Number of satisfactory ratings	0	0
	1–2	14
	3–5	26
	6 or more	33
Number of 90-day ratings + derogatory items	0	129
	1	34
	2	13
	3 or more	0
Number of past due balances	0	38
	1	7
	2 or more	0
Number of credit cards	0	0
	1–3	40
	4 or more	53
Credit card balances reported in last 12 months	$0 to $250	40
	>$250 to $1,000	37
	>$1,000 to $3,000	17
	>$3,000 or more	0

Minimum possible score = 0 Maximum possible score = 511

Source: Lawrence & Solomon 2013

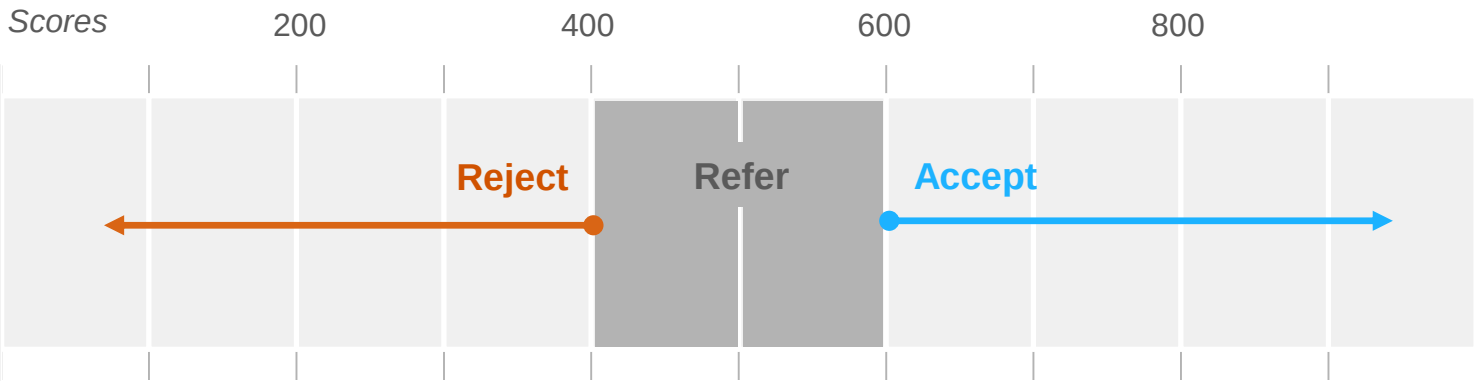
How To Use A Scorecard?

PHOTO CREDIT: Malik Asim Mansur, 2008 CGAP Photo Contest

Setting Cutoffs: A Business Decision

Organizations set a **minimum score requirement** to accept applicants. This minimum score is called “cutoff” and represents a threshold of risk appetite.

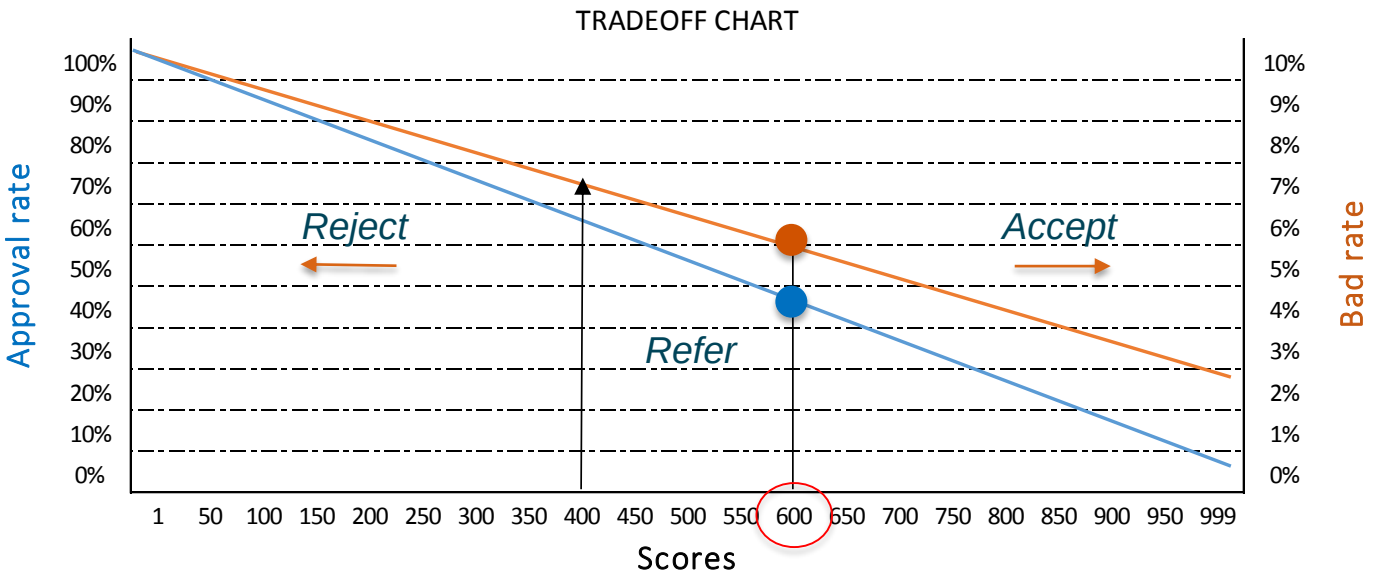
In the example below, an applicant with a credit score of 400 and below will be rejected, 400-600 referred, and 600 and above accepted.



Setting Cutoffs: A Business Decision

Setting a cutoff is a matter of **balancing risk versus growth**. In some cases, a lender might want to increase its customer base by increasing its approval rate, even though this might negatively affect the default rates.

A “tradeoff chart” may help visualize and strategize these dependencies.

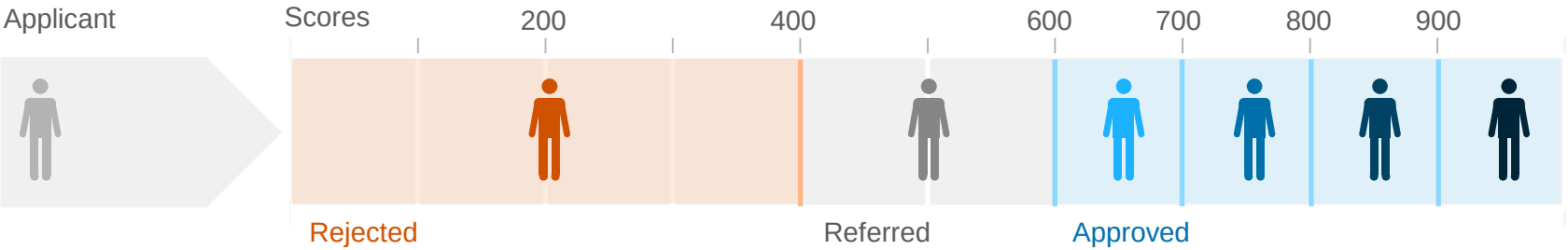


In this example, a **cutoff at 600+** translates into an approval rate of **45%** with a bad rate of **6%.** In other words, you accept 45% of all applicants, out of which 6% are likely to default.

Integrating scores into a decision funnel

Scores will support your decision management, but for this to work, you will need to integrate the scorecard into a decision funnel.

Here an example:



If score between: 400–599, offer:

PRODUCT: **A**

INTEREST RATE: **8%**

CONDITIONS: **MORE THAN $100 IN SAVINGS**

If score between: 600–699, offer:

PRODUCT: **A**

INTEREST RATE: **8%**

PRODUCT RENEWAL FEATURES: **REAPPLICATION REQUIRED**

If score between: 700–799, offer:

PRODUCT: **A**

INTEREST RATE: **6.5%**

PRODUCT RENEWAL FEATURES: **REAPPLICATION REQUIRED**

If score between: 800–899, offer:

PRODUCT: **B**

INTEREST RATE: **6%**

PRODUCT RENEWAL FEATURES: **AUTOMATIC RENEWAL**

If score is greater than 900, offer:

PRODUCT: **B**

INTEREST RATE: **5%**

PRODUCT RENEWAL FEATURES: **AUTOMATIC RENEWAL**

How Do I Know a Scorecard Works?

PHOTO CREDIT: Md. Fakrul Islam, 2012 CGAP Photo Contest

How do I know if I have a scorecard that works?

Once a scorecard is assembled, it is time to test its predictive power. There are a few ways to measure its performance.

Confusion Matrix

The model will project probabilities of default, so at an aggregate level, we can check how many of those who the model predicted as bad were actually bad, as well as goods.

		Actual	
		Low credit quality	High credit quality
Model	Low credit quality	Correct Prediction (46%)	Error (6%)
	High credit quality	Error (5%)	Correct Prediction (44%)

Both error types carry quite different consequences for the business:

Could be a potential **loss of profits** (the model predicted Low Credit Quality when was actually a High Credit Quality).

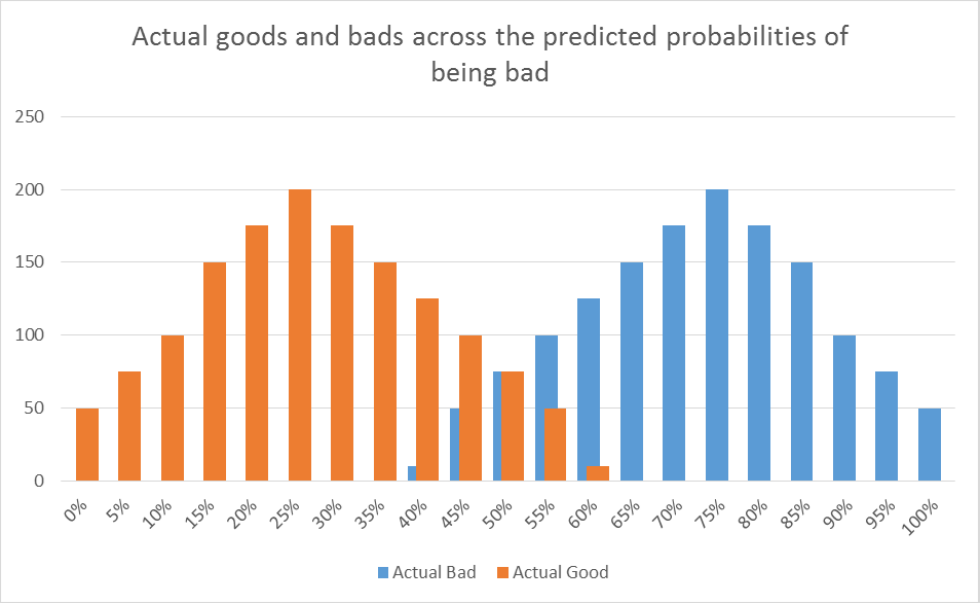
Could also be a potential **loss of interests + principals + recovery costs** (the model predicted High Credit Quality when was actually a Low Credit Quality).

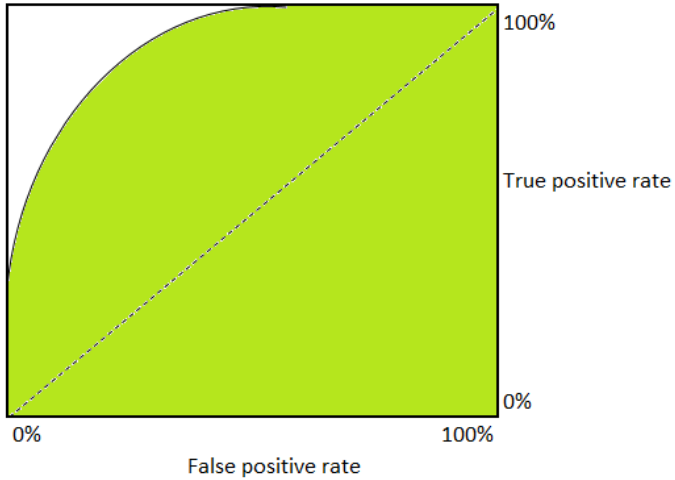
The accuracy in this table equals 89%. The error then, or misclassified cases, counts for 11%.

How do I know if I have a scorecard that works?

Area under the Curve (AUC)
ROC curves are built to get to the AUC metric, which is another way to measure the accuracy of a credit scorecard.

Below, you can see a distribution of actual goods and bads across the predictive probabilities.





The AUC measures the percentage of the box that is under this curve (in green). The higher the percentage the better, which translates into a more accurate scorecard.

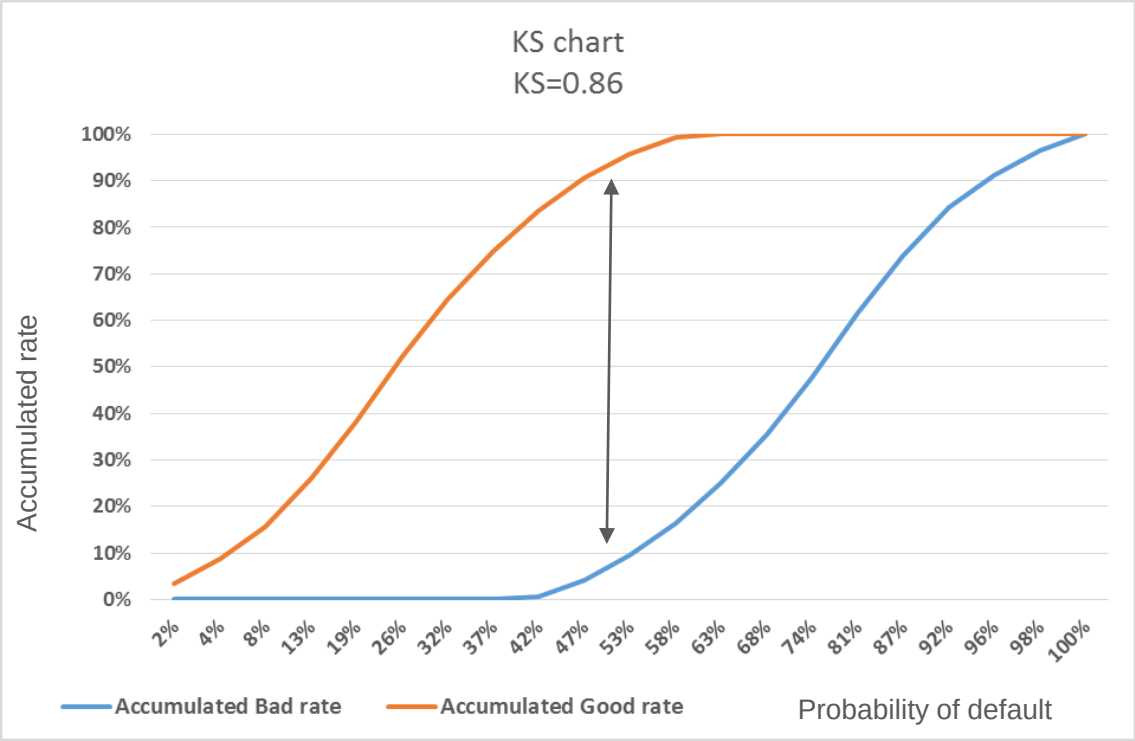
The ROC curve is built by plotting the True Positive Rate:True Positives/All Positives (on the y-axis); versus the False Positive Rate, and False Positives/All Negatives (on the x-axis) for every possible classification threshold.

How do I know if I have a scorecard that works?

Kolmogorov-Smimov or KS Metric

The KS test measures the maximum vertical separation between two cumulative distributions (good and bad) in a credit scorecard.

The higher the separation between the two lines the higher the KS which translates into a more accurate scorecard.



How do I know if I have a scorecard that works?

Some benchmarks

- **Confusion matrix**: The result of a confusion matrix needs to be greater than 50%.
- **KS**: The standard for a good model will be a KS greater than .50, but in some cases where you don't have enough data, you can also work with KS's that are just over .25.
- **Area Under the Curve**: Here anything above .75 will be considered a good model.

The most common software tools that are used in credit scoring are: SPSS, SAS, STATA, and R.

Data Sources

PHOTO CREDIT: Rabin Chakrabarti, 2012 CGAP Photo Contest

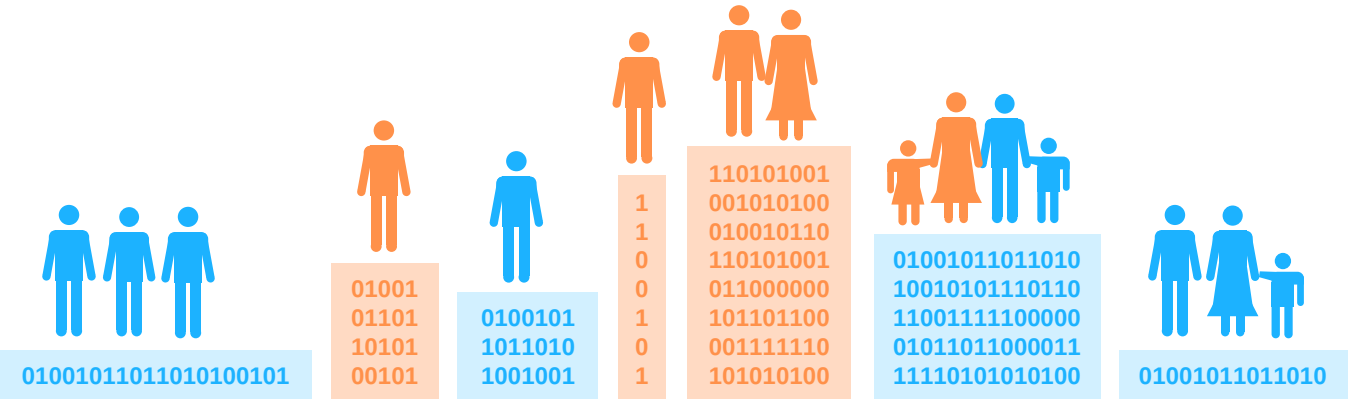
Old vs. new school of credit scoring

Traditionally, banks and credit card companies were the only players conducting credit scoring.

Today new actors and partnerships that combine their strengths are leveraging credit scoring.

These new actors are generating and collecting alternative types of data.

Telecoms, **SmartPhone handsets** and **social media** are new sources of data that are being leveraged for credit scoring.



Structured vs. unstructured data

Generally, there are two types of data: Structured and unstructured.

Structured data
Refers to information that has a high degree of organization such as rows & columns. It is most likely included in a relational, easily readable and searchable database, e.g. Excel spreadsheet.

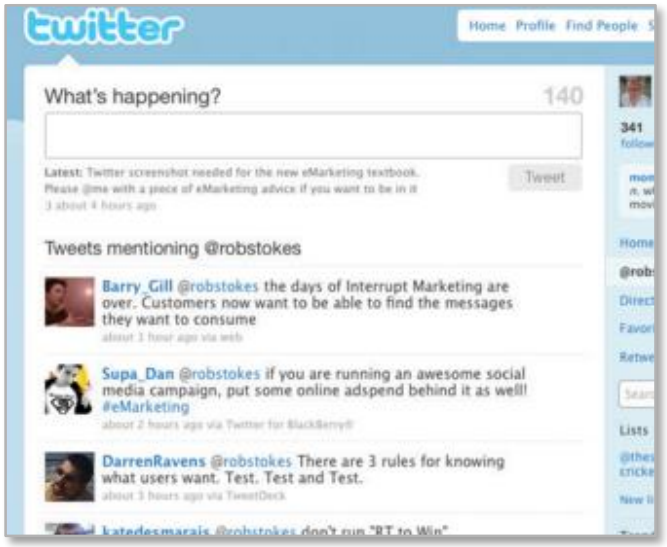
Unstructured data
Is the exact opposite, i.e. data that cannot fall within the typical row and column format of any database, e.g. Email: Even if your inbox is arranged by date, time or size, it cannot be arranged by exact subject and content. Images and multimedia are also good examples of unstructured data.

It is believed that between 80-90% of the information in a business is unstructured in nature.

Structured

CUSTOMER	CUSTOMER_TYPE	CUST_BRANCH	DATE_APPLIED	DATE_APPROVED	DATE_OPENED
4443139	NORM	0003	12-Nov-2009	12-Nov-2009	12-Nov-2009
4443139	NORM	0003	18-Sep-2014	27-Oct-2014	27-Oct-2014
4443139	NORM	0003	.	27-Oct-2014	27-Oct-2014
4443139	NORM	0003	.	12-Jul-2004	12-Jul-2004
4443139	NORM	0003	.	28-May-2006	28-May-2006
4443139	NORM	0003	.	04-Aug-2013	04-Aug-2013
4443139	NORM	0003	12-Nov-2009	12-Nov-2009	12-Nov-2009
4443139	NORM	0003	18-Sep-2014	27-Oct-2014	27-Oct-2014
4443139	NORM	0003	.	27-Oct-2014	27-Oct-2014
4443139	NORM	0003	.	12-Jul-2004	12-Jul-2004
4443139	NORM	0003	.	28-May-2006	28-May-2006
4443139	NORM	0003	.	04-Aug-2013	04-Aug-2013
4443140	NORM	0003	05-Apr-2010	05-Apr-2010	05-Apr-2010
4443140	NORM	0003	.	18-Jul-2004	18-Jul-2004
4443140	NORM	0003	.	20-Apr-2006	20-Apr-2006
4443140	NORM	0003	05-Apr-2010	05-Apr-2010	05-Apr-2010
4443140	NORM	0003	.	18-Jul-2004	18-Jul-2004
4443140	NORM	0003	.	20-Apr-2006	20-Apr-2006
4443141	NORM	0003	.	05-Sep-2004	05-Sep-2004
4443141	NORM	0003	.	14-Jun-2009	14-Jun-2009

Unstructured

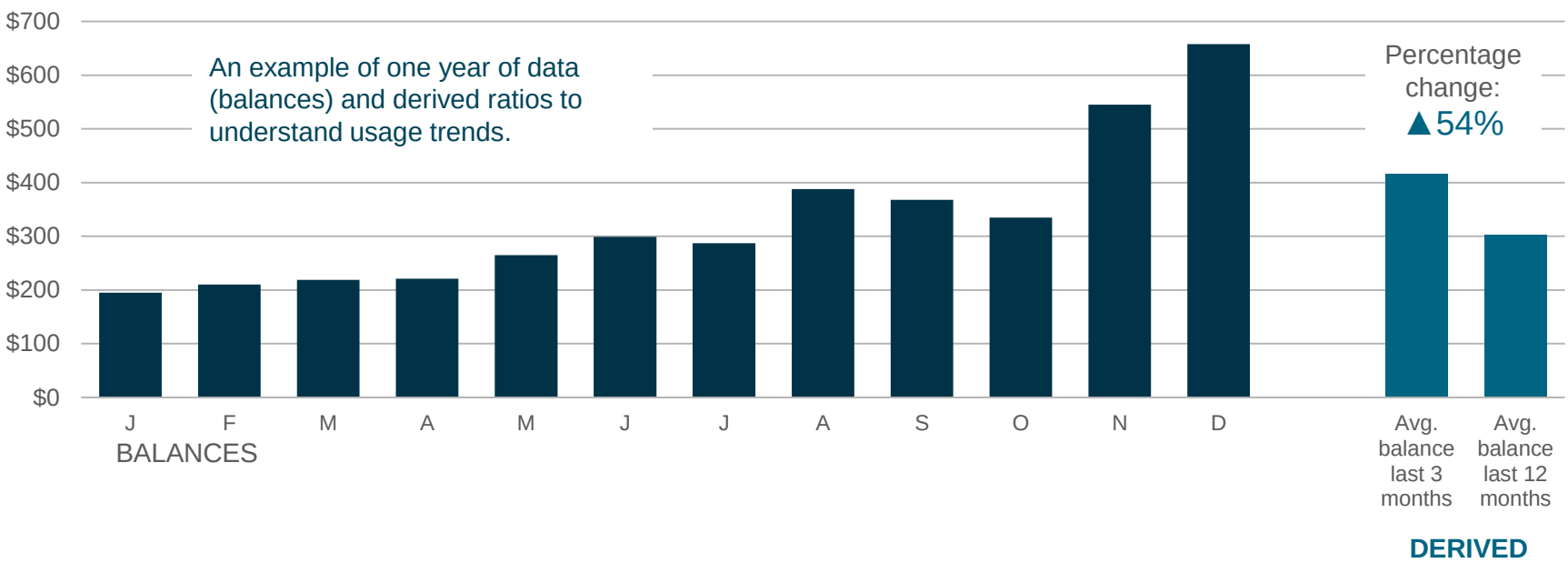


From digital data trails to customer behaviors

In digital credit, most data (if not all) is collected in digital format and within a well-defined structure.

Data modeling is part science and part art, because it requires a great deal of creativity to derive useful information from the original data.

Calculated variables and ratios that measure customers' behaviors are called *derived* variables. These derived variables are usually the ones used for developing a credit scorecard.



How much historical data should I use?

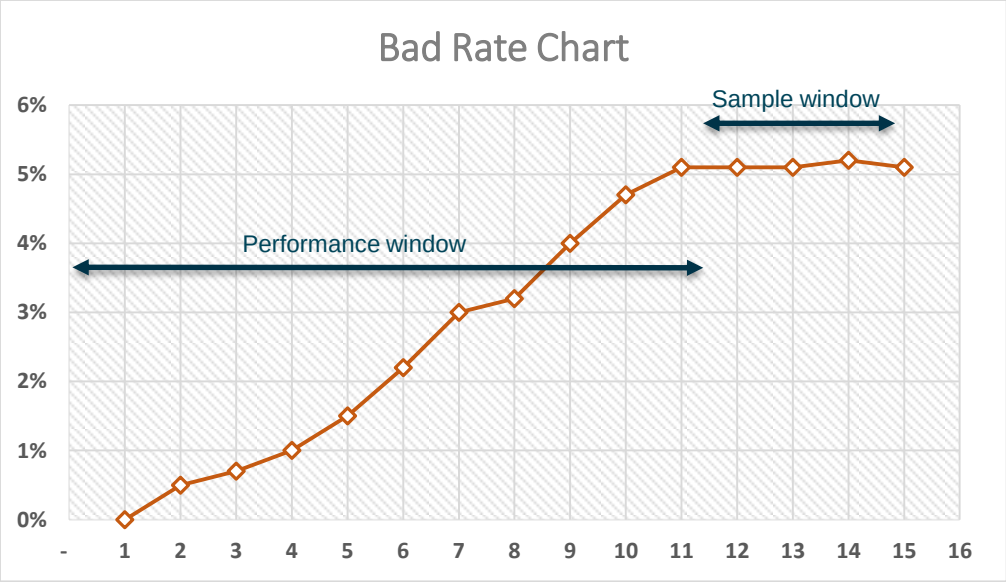
Bad Rate Charts

Due to the shorter loan terms, performance tracking of digital credit can be done much quicker than with conventional, longer-term loans.

In this case, the bad rate stabilizes after month 10, which means that you will need to include accounts opened at least 12 months ago and then track back their performance.

With digital credit, your performance window may be shorter, and your sample window could start after e.g. month 3.

Selecting the sample from a mature cohort is done primarily to ensure that <u>all accounts have been given enough time to “go bad”.</u>



Types of Data

Call Data Records (CDRs)
CDRs are “transactional” records as they capture every single operation the user performs.

METRIC OR INDICATOR	PROXY
Socio-demographic information	Age, Gender, and Location
Number of calls and SMS both emitted and received	Income
Usage level over time (increasing or decreasing usage)	Income Flows and Variability
Airtime top-up (average balances, amounts, periodicity)	Income, Obligation-planning and Risk
Geocoded location	Location, Movement, and Income
Customer since date (using the oldest transaction)	Risk
Size of user’s network, and location	Social Network and Risk
Duration of calls and pattern (day use, weekend use, etc.)	Social Profile

With this small trail of data, we could eventually extract the following indicators and proxies.

Figure 13 – Example Set of CDR Fields

Calling Party Number	Called Party Number	Caller Cell ID	Location Area Code	Call Time	Call Duration	Served IMSI
25358XXX	25358XXX	5102	41708	2012-12-06 14:24:32	01:25:34	4600013511068690

Note: This is a coarse representation of a complete CDR. Many typical fields are stripped for brevity.

Source: *Using Mobile Data for Development*, Cartesian and Bill & Melinda Gates Foundation, 2014

Types of Data

Mobile Money Transactions
Businesses offering mobile money services capture the transactional activity of their users.

Transaction reference #
Amount
Fee
Status (paid, sent, refunded)
money transfer collection location
Send date/time
Sender ID
Sender Name
Sender Surename
Sender Mobile number
Sender Gender
Sending Agent
Commission for sending Agent
Sending Agent location town
Sending Agent location province
Cashout date
Recipient ID
Recipient first name
Recipient surname
Recipient mobile
Recipient gender
Cashout agent company name
Cashout agent commission
Cashout agent location town
Cashout agent location province

METRIC OR INDICATOR	PROXY
Customer since date	Risk
Number of different agents used, sent and cash out	Customer and Agent Cost
Socio-demographic information	Age, Gender and Location
Socio-demographic information sender and receiver	Gender and Location
Geocoded location sent and received	Location, Movement and Income
Size of user's agent network, and location	Agent Network
Size of user's network, and location	Social Network
Usage pattern (day use, weekend use, etc.)	Social Profile
Average savings, and frequency for sending, receiving and keeping funds in the account	Income Flows and Collateral
Number of transactions sent and received, volume and average amounts, fees, trends.	Income Flows, Customer Value and Cost

Types of Data

Utility/Electric Bills
The example below presents the type of data an electric company collects from its customers and the metrics and proxies contained.

In developed markets, big scoring companies are already producing credit scorecards based on data derived from utility companies.

These alternative approaches can open the door to financial inclusion to numerous individuals who do not have a credit history.

Bill #
Customer #
Customer ID (SSN, Nat. ID)
Customer address
Customer area code
Year
Month
Average temperature
Heating Degree Days
Cooling Degree Days
Total charge (per kwh)
Calculated consumption (in kwh)
Amount of bill
Payment type (check, automatic debit)
Balance

METRIC OR INDICATOR	PROXY
Consumption level	Income and Customer Value
User location	Income
Usage pattern (day use, weekend use, etc.)	Social Profile
Household size	Social Profile
Socio-demographic information	Age, Gender and Location
Customer since date, changes in address	Planning and Risk
Payment type, credit card (yes, no)	Banked or Unbanked
Balance due	Obligation-planning-risk

Types of Data

Social Media
A few companies are using social media data for scoring. This is relatively new, but most of the data included is structured.

Facebook and Twitter are examples of platforms used to extract valuable information about users and potential customers. Additionally, these companies can analyze the type of device you use to connect to those platforms, which adds additional data points.

METRIC OR INDICATOR	PROXY
User since date	Income, Tech Profile, And Risk
Frequency and recency of posts emitted and received	Income
Size of user's network, and location	Social Network And Risk
Geocoded location	Location, Movement, Income And Risk
Posts patterns (day use, weekend use, etc.)	Social Profile
Sociodemographic information	Age, Gender And Location
Device types	Income, Tech Profile And Risk

Types of Data

Credit Bureau Data (Positive and Negative)
Credit bureaus collect information from the market they operate in, and have access to multiple sources of data beyond the banking sector.

Credit bureaus compile up to 1,500 variables per individual, although in some cases some of those variables may not contain any information.

On the other hand, they collect both positive and negative information; this means that banks do not only report when you are overdue, but also each of your credit lines and usage levels on a monthly basis.

METRIC OR INDICATOR	PROXY
Customer since date	Risk
Number of inquiries	Risk
Employment data	Risk
Number, credit limits and usage of active credit lines	Income and Risk
Performance data on repayment of active accounts	Income and Risk
Sociodemographic information	Age, Gender and Location

Credit Scoring: Summary Points

- Credit scoring helps calculate the **probability of default**. It is only **one of several risk management tools**;
- There are **different scorecards** linked to the kinds of decisions to be made and data used;
- Building a scorecard requires **deep expertise** linked to a **business strategy**;
- There is a **process to build scorecards** for digital credit, and specific statistical tools to **measure the predictive power** of scorecards;
- The **sources of data are rapidly changing** in a digital world, requiring new analytic techniques.

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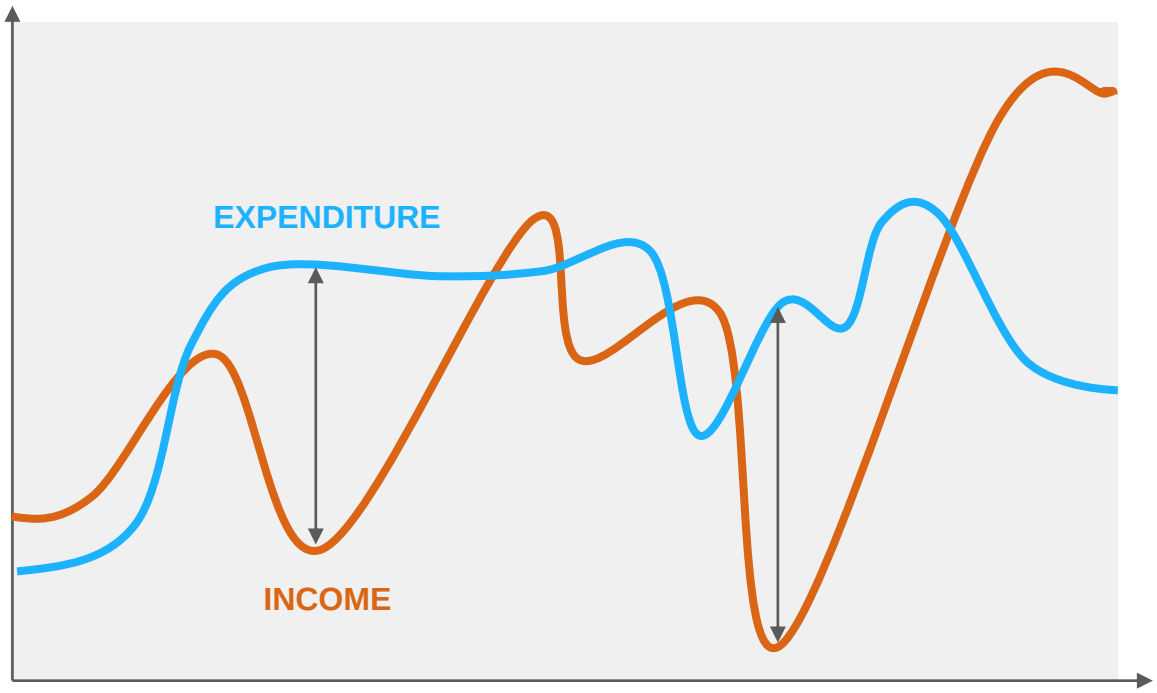
Understanding Customer(s) and their Financial Needs

PHOTO CREDITS (clockwise from top left): Syed Mahabubul Kader Imran, 2015 CGAP Photo Contest; Joseph Molieri, 2012 CGAP Photo Contest; Logan Dickerson, 2015 CGAP Photo Contest; Mohammad Saiful Islam, 2015 CGAP Photo Contest; Rana Pandey, 2015 CGAP Photo Contest; Hailey Tucker, 2015 CGAP Photo Contest

Target Market: Informal Sector

Fluctuating and volatile income and expenditure streams create the need for **short-term liquidity** to help bridge temporary income gaps.



Voices of the Customer

Some excerpts from actual M-Shwari users:

"My son was bleeding a lot from the nose and I was just back from the market and had used all of the money. I needed $12 and that money helped a lot."

"My salary delayed and my house help needed money so what did I do? I borrowed $30. I paid the house help with part of it and with another part I paid the motorcycle person who carries my baby to and from school."

"I am in transport business. Not all the time do I have money, so I can borrow money to help out my drivers when they are caught by the police."

"M-Shwari for me is just for small savings and borrowing for things like airtime, not major items."

Source: Kenya Financial Diaries, FSD-Kenya

Product Design

PHOTO CREDIT: Mohammad Moniruzzaman, 2012 CGAP Photo Contest

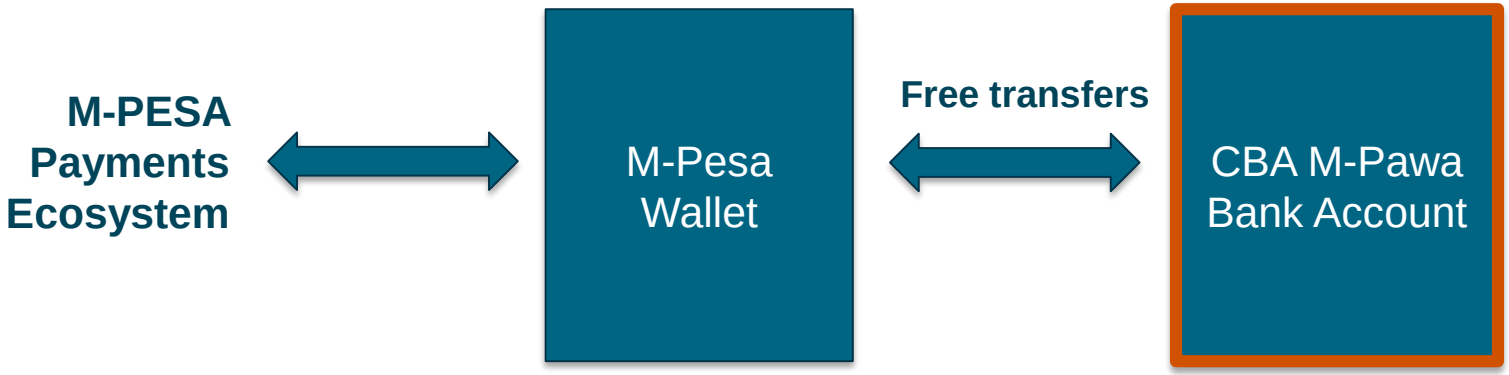
Product Design Options

Link Savings with Credit?

Advantages:

- Flexibility for client
- Additional source of funding
- Learn more about customer behavior (data)
- Allow clients to separate wallet from savings

For example, in Tanzania:



Product Design

Loan Term Options

For example:

- Inflexible fixed term or choice
- Option to extend loan term at point of maturity
- Repayment terms

	M-Shwari	nimetimiza loans at your fingertips	ECOCASHLOANS	Instaloan
LOAN TERM:	4 weeks	1, 2, 3, or 4 weeks	4 weeks	16 weeks

Product Design

Loan Limits

For example:

- Limits may vary by credit score
- Loan sizes increase with positive history
- Should weigh carefully how limits are communicated to customer

	M-Shwari	nimetimiza loans at your fingertips	ECO CASHLOANS	Instaloan
TYPICAL:	USD $30	USD $10	USD $125	USD $50

Product Design

Pricing Options

For example:

- Subscription fee
- Simple flat fee
- Simple fee tied to loan amount
- Interest rate tied to loan amount
- Fees associated with extending the loan or late payment
- Dynamic pricing: based on borrowers score, loan amount and prior history (complex and sophisticated)

	M-Shwari	nimetimiza loans at your fingertips	ECOCASHLOANS	Instaloan
INTEREST/FEE:	7.5% monthly	0.5% a day	5% handling	10% monthly
ADDITIONAL FEES:	None	10% initiation fee	Transaction fees for moving funds to/from wallet	One time application fee

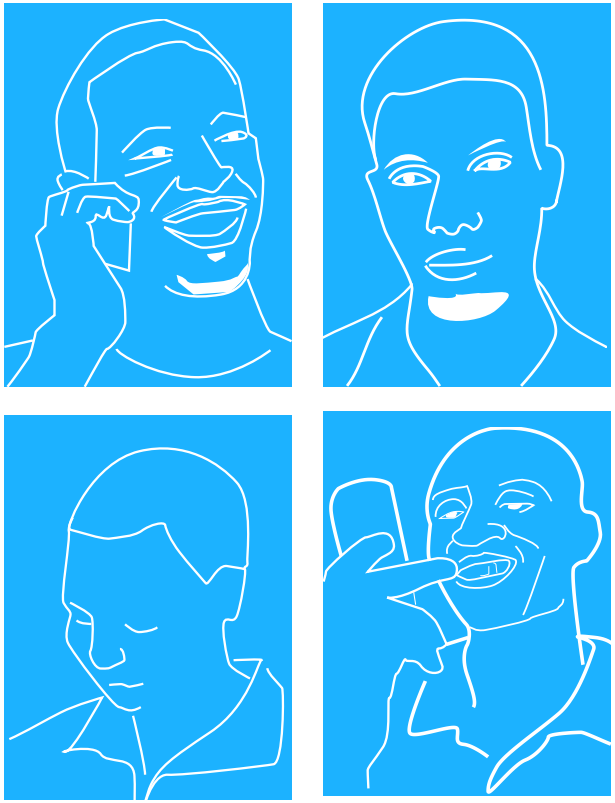
Consumer Protection

PHOTO CREDIT: Roberto Huner, 2014 CGAP Photo Contest

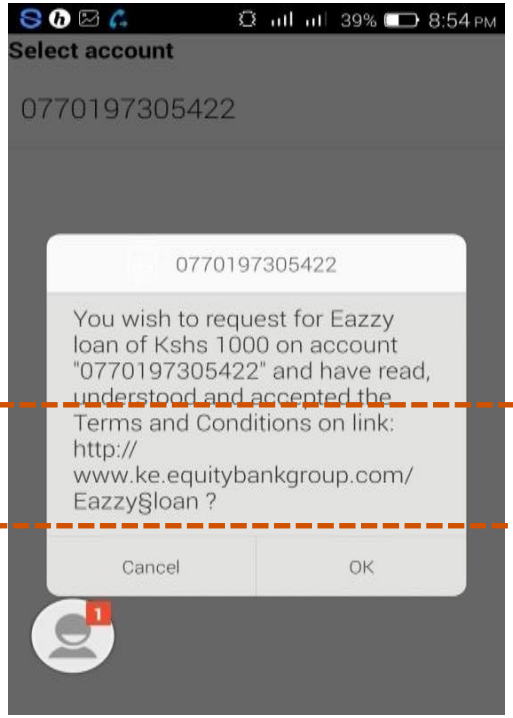
Consumer Protection

A number of consumer protection challenges must be addressed when designing a service, including:

- **Transparency** on terms, conditions, fees, and customer rights;
- **Disclosure** requirements;
- Accounting for limited general **literacy and numeracy**;
- **Data ownership** and **data privacy** challenges.



Examples: Transparency & Disclosure of Terms



Open the URL to view Terms and Conditions

Information released post-purchase

- What about those with feature phones?
- Areas without internet connectivity?

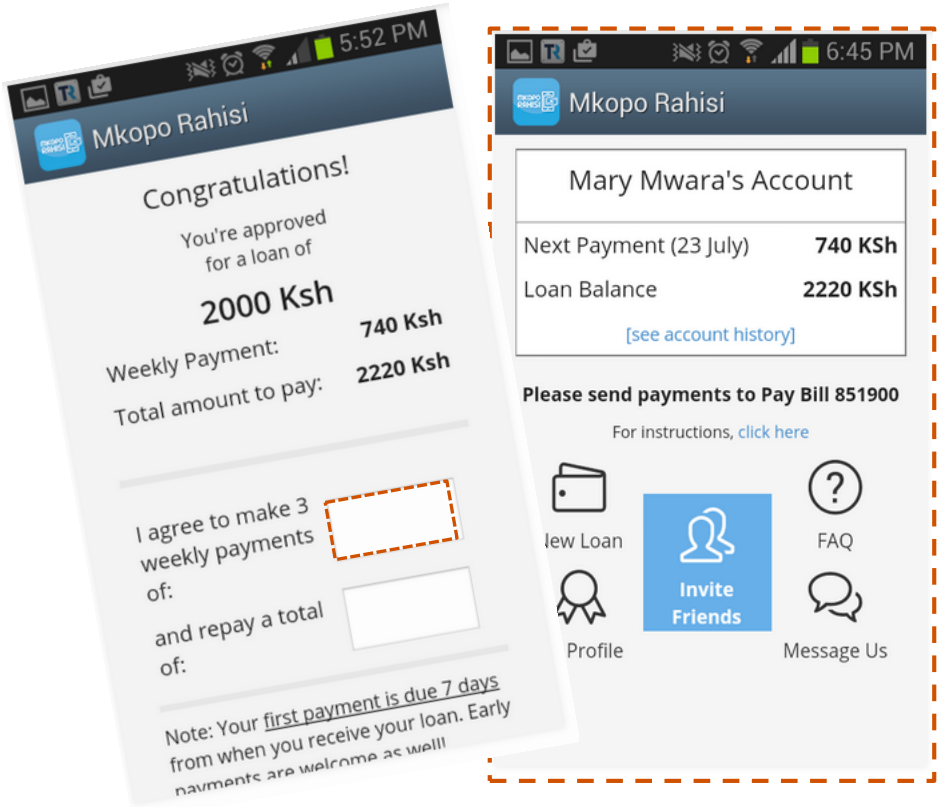
- Most borrowers think that the interest rate on loans is 2%
- However, varies between 2%-10%
- In this case: 6%.

Examples: Transparency & Disclosure of Terms

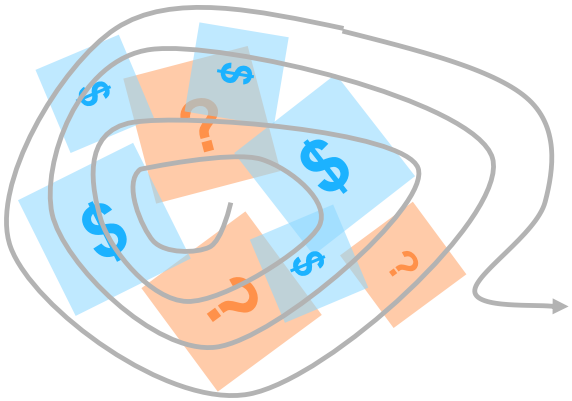
An example of a good breakdown of cost and payment schedule:

Clear display of:

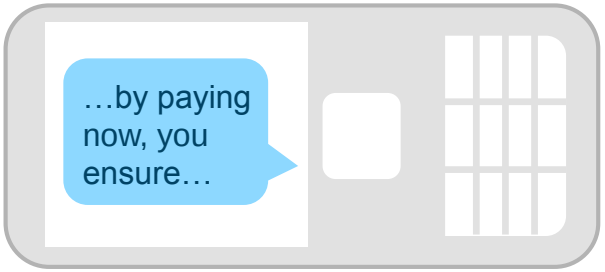
- Loan amount approved
- Interest amount charged
- Repayment period
- Option to agree/disagree with terms and conditions



CGAP Experiments: Reducing Delinquency and Increasing Repayment Rates



1. Framing of product costs made consumers more likely to review these terms, and reduce delinquency.

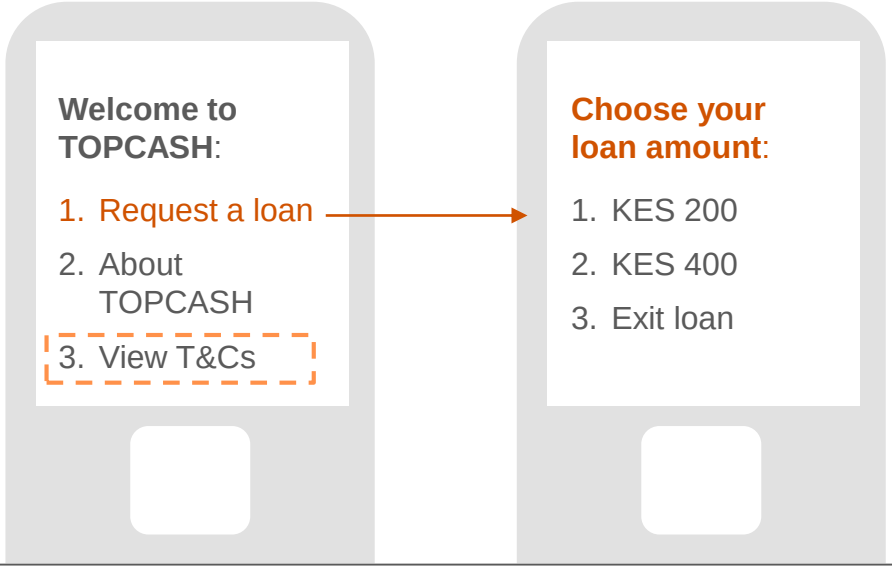


2. Timing of SMS and behavioral “nudges” in repayment reminders can increase repayment rates.

Active Choice Approach Increases Viewing of T&Cs

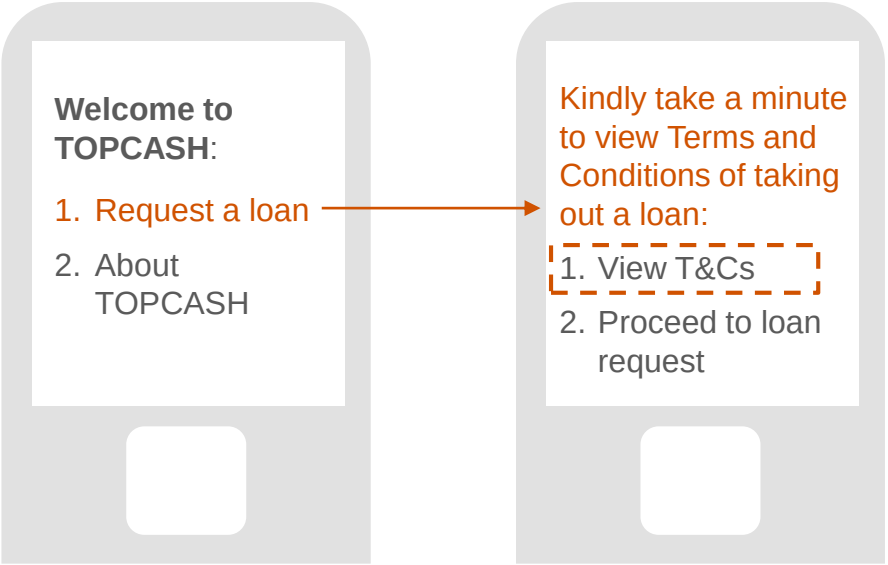
Without active choice

Borrowers select:
"Request a loan"



With active choice

Borrowers select:
"Request a loan"



Terms and Conditions viewing increased from 10% to 24% by making it an active choice.

Separating Finance Fees Leads to Better Borrowing Decisions

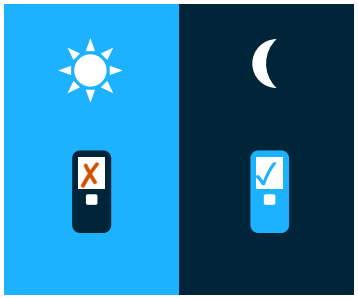
Choose your repayment plan:
1.Repay 228 in 45 sec
2.Repay 236 in 1min and 30sec
3.Repay 244 in 2min and 25sec

vs.

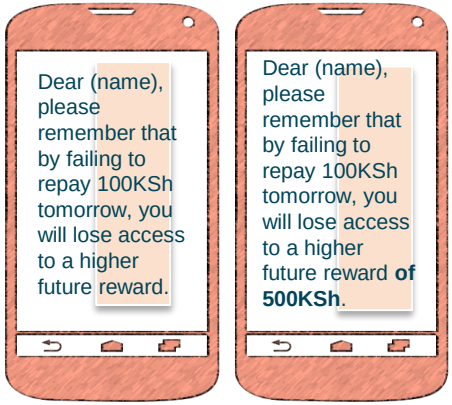
Choose your repayment plan:
1.Repay 200 + 28 in 45 sec
2.Repay 200 + 36 in 1min and 30sec
3.Repay 200 + 44 in 2min and 25sec

Clarifying interest rates led to a **reduction in default rates** on first loan cycles from **29.1% to 20%**

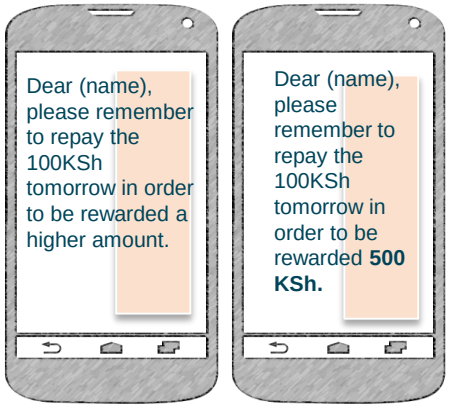
Reminder Message Framing and Repayment Effects

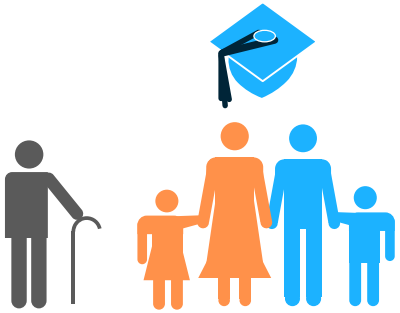


Timing and Planning
Respondents who received evening reminders were 8% more likely to repay their loan than in the morning

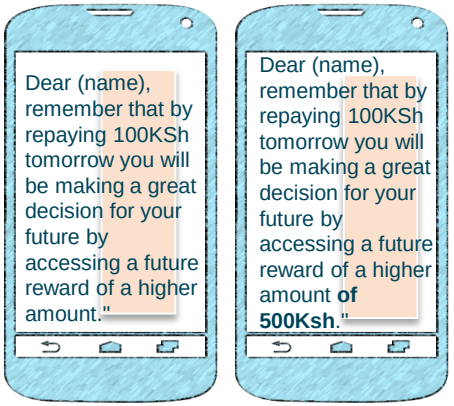


Gender Effects
Treatments had a significant positive effect on men, but a significant negative effect on women.





Education and Age
Goal savings had a positive (but not significant effect), but this was significant among the educated and older groups.



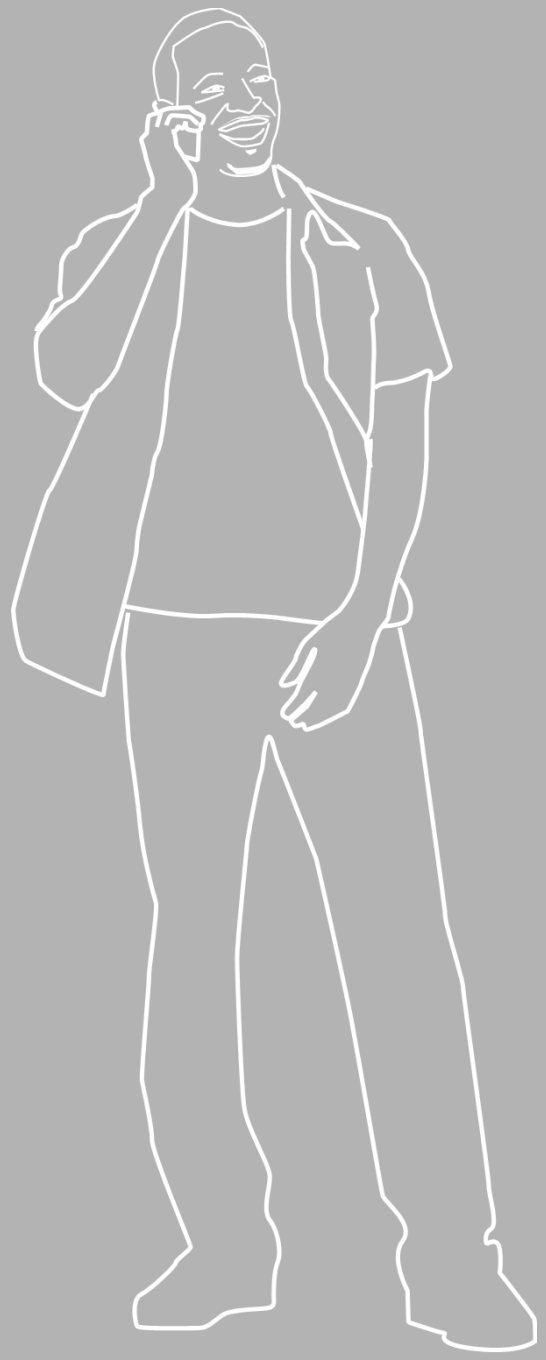
Recommendations

Transparency, Disclosure and Consumer Empowerment

- Provide all information necessary for the client decision-making process **pre-purchase**;
- Write Terms and Conditions in a **clear and straightforward** manner;
- **Standardize** fee names and disclosures related to the services;
- Conduct **consumer testing** to check effectiveness of behavioral nudges;

Remember:

- Positive borrower outcomes can align with business interests,
- Yet simplicity is a virtue!



Digital Data: Opportunities and Risks

Digital data can help many unbanked consumers enter the formal financial sector, thus address barriers to entry.

However, several questions need to be addressed, including:

- **Data ownership**: Who “owns” customer data? Are there distinctions between mobile phone, internet, and financial transactions data?
- **Data security**: Who is responsible and liable?
- **Informed consent and recourse**: What data are customers willing to share? How can customers correct false information?

“Each time you visit one of our Sites or use one of our Apps we may automatically collect the following information… information stored on your Device, including contact lists, call logs, SMS logs…”

—Excerpt from privacy policy of Kenyan digital lender

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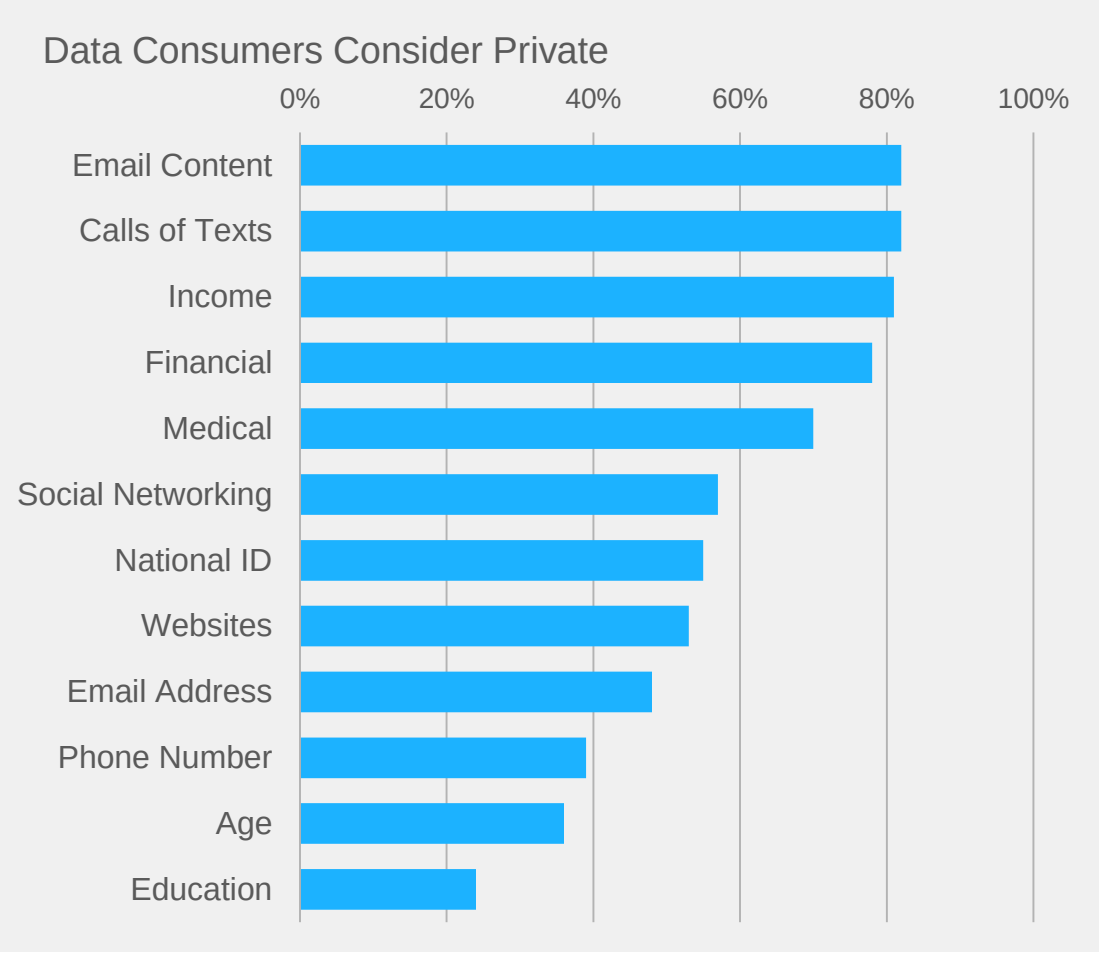
“Big Data, Small Credit”

Findings from Omidyar Network Consumer Survey in Kenya & Colombia:



Information Consumers are Willing to Share to Improve their Chances of Getting a Loan or a Bigger Loan

7 out of 10

Mobile phone use and bank account use

6 out of 10

Social media activity and web browsing history

Source: Omidyar Network (2015), “Big Data, Small Credit”

Example: First Access

Features

- 100% via SMS
- Consumers opt-in to allow mobile and other records to be used for credit score
- One-off: Consumer only opts in for single usage of their data

SMS Disclosure Approved by Regulators

"This is a message from First Access: If you just applied for a loan at Microfinance Bank and authorize your mobile phone records to be included in your loan application, Reply 1 for Yes. Reply 2 for more Information. Reply 3 to Deny."

Example: First Access

Supplemental educational sheet:

How First Access works with your Lender

first access

1. You apply for a loan at a financial institution
2. Your loan officer texts your mobile number to First Access
3. First Access sends you a text message
4. You decide if we may use your mobile phone records (reply "1" if yes)
5. First Access makes a loan recommendation to your loan officer by text message

Questions? Contact your loan officer or call First Access at 12345678.

Mobile phone records

Information captured when you use your phone. Examples include:

- ✓ Phone calls
- ✓ Airtime top-up
- ✓ Mobile money
- ✓ Texts
- ✓ Bill pay

How we keep your mobile data safe

First Access will *never* share your personal information with anyone.

First Access will *never* read your text messages or hear your calls.

***Never* send First Access your phone number, PIN, or bank details. We will never ask for that information.**

Note: All documents and SMS' tested in Swahili version

For more information, see CGAP Publication: Informed Consent How Do We Make It Work for Mobile Credit Scoring?

Consumer Risks – At a Glance

Disclosure and transparency

- Fees and pricing
- Terms and conditions
- Penalties and delinquency management

Data privacy and data ownership

Push marketing and aggressive sales practices

Service Design: Summary Points

- Build a clear picture of **who** you are trying to reach and **how** the service will appeal;
- Given irregular income flows, mass market customers often have **short-term liquidity needs**;
- There are a range of **product design options**;
- Build **consumer protection** principles into design from the start; small details matter.

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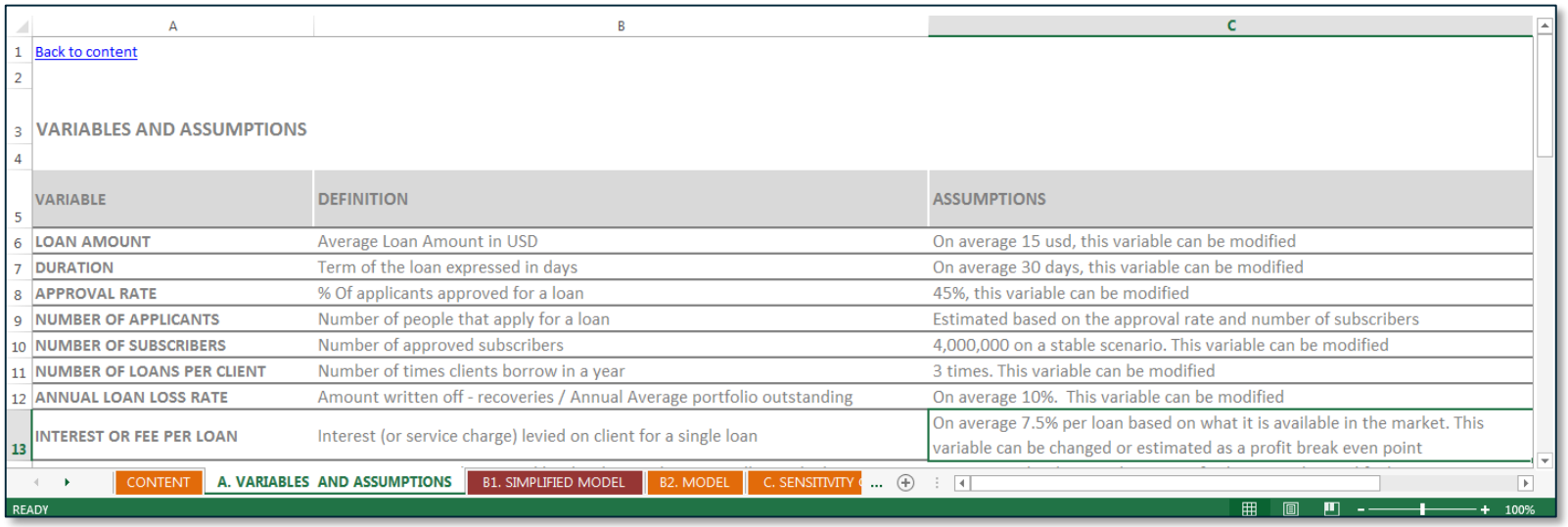
A Financial Model for Digital Credit

CGAP has built a basic Excel-based **Financial Model for Digital Credit**. This can be used to estimate steady state level profitability. It may be a useful starting point for providers who are looking to build projections for their own services.

To get a copy of the Financial Model for Digital Credit (Excel), please send an email to cgap@worldbank.org with a subject heading “Digital Credit Financial Model”.



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VARIABLES AND ASSUMPTIONS

VARIABLE	DEFINITION	ASSUMPTIONS
LOAN AMOUNT	Average Loan Amount in USD	On average 15 usd, this variable can be modified
DURATION	Term of the loan expressed in days	On average 30 days, this variable can be modified
APPROVAL RATE	% Of applicants approved for a loan	45%, this variable can be modified
NUMBER OF APPLICANTS	Number of people that apply for a loan	Estimated based on the approval rate and number of subscribers
NUMBER OF SUBSCRIBERS	Number of approved subscribers	4,000,000 on a stable scenario. This variable can be modified
NUMBER OF LOANS PER CLIENT	Number of times clients borrow in a year	3 times. This variable can be modified
ANNUAL LOAN LOSS RATE	Amount written off - recoveries / Annual Average portfolio outstanding	On average 10%. This variable can be modified
INTEREST OR FEE PER LOAN	Interest (or service charge) levied on client for a single loan	On average 7.5% per loan based on what it is available in the market. This variable can be changed or estimated as a profit break even point

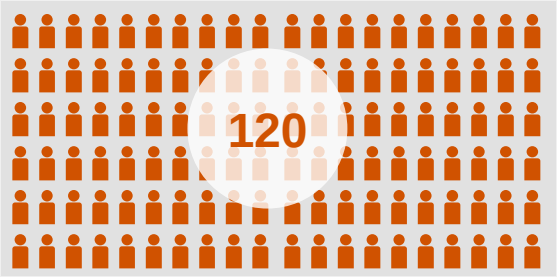
Financing Small Short Term Loans

PHOTO CREDIT: MD Khalid Rayhan Shawon, 2012 CGAP Photo Contest

Short term loans require much less capital

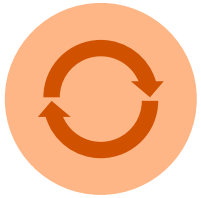
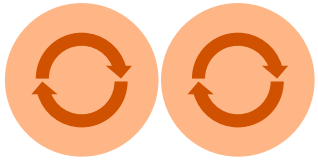
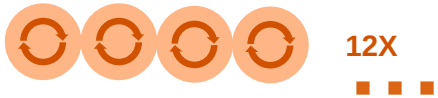
Base Assumptions:

Number of borrowers



Loan size

Number of loans per year

	1 year	6 months	1 month
Loan Term:			
Annual Disbursements:	$120,000	$120,000	$120,000
Loan Capital Required (US$):	$120,000	$60,000	$10,000

Short term loans require much less capital

Base Assumptions:

Number of borrowers	Loan size	Loan term	Number of loans per year
4 million	US$15	30 days	three

Annual Disbursements:

Number of borrowers × Average loan size × Number of loans per year = US$ 180,000,000

4 million × US$ 15 × three = $180 million

Required Loan (Portfolio) Capital:

Number of borrowers × Average loan size × Loans outstanding at any given moment = US$ 14,794,521

4 million × US$ 15 × three × 30 days ÷ 365 = 0.247 = $15 million

A Financial Model

PHOTO CREDIT: KM Asad, 2012 CGAP Photo Contest

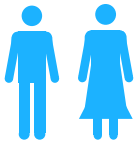
A Financial Model: Costs

The cost structure of digital credit deployments **does not** require brick and mortar bank branches and bank staff in the physical locations.

However, a number of operational costs need to be taken into consideration, including (but not limited to):

Data (in case you need to buy customer data from another party)

Credit scoring (developing and maintaining a scoring system)



Management (staff dedicated to planning, design and maintenance of product)

Communications (e.g. SMS and call reminders)

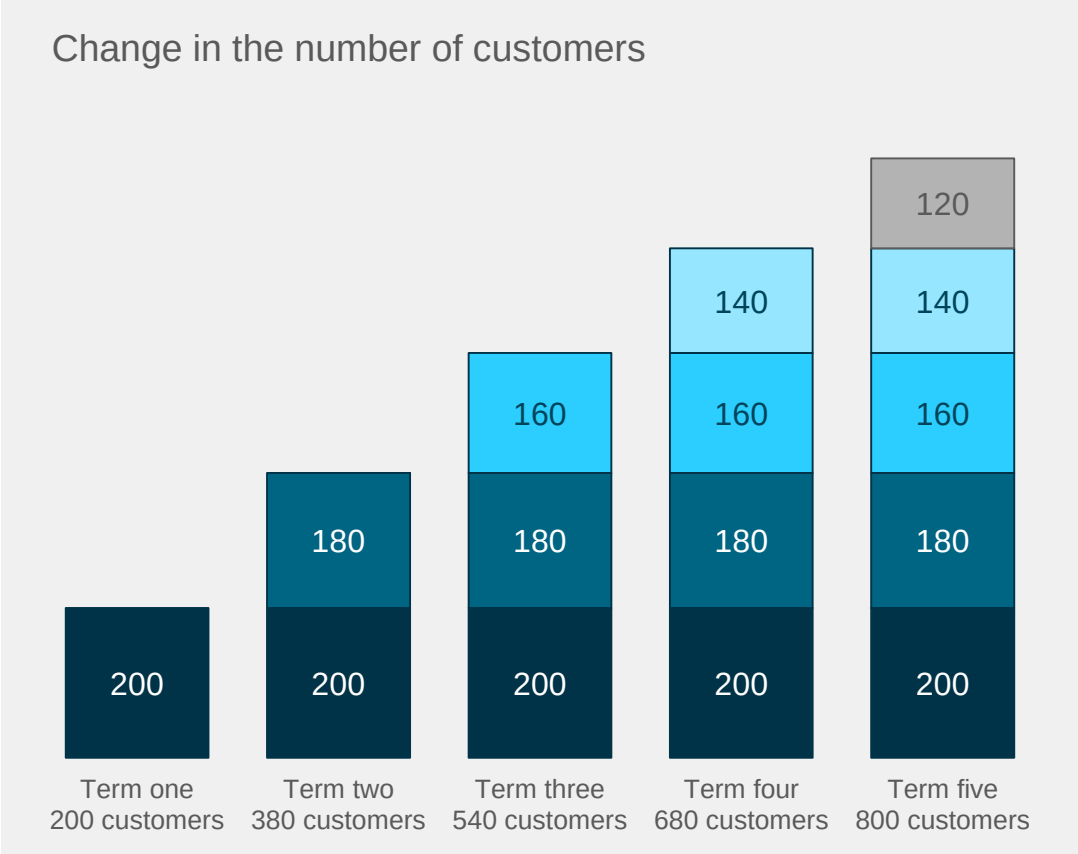
Payments (e.g. transaction fees charged on MM payments)

Call center

A Financial Model: Portfolio Evolution

Your loan portfolio will evolve and mature over time. Even as some attrition occurs, the total customer base will grow and borrowers can take on bigger loans.

Illustrative

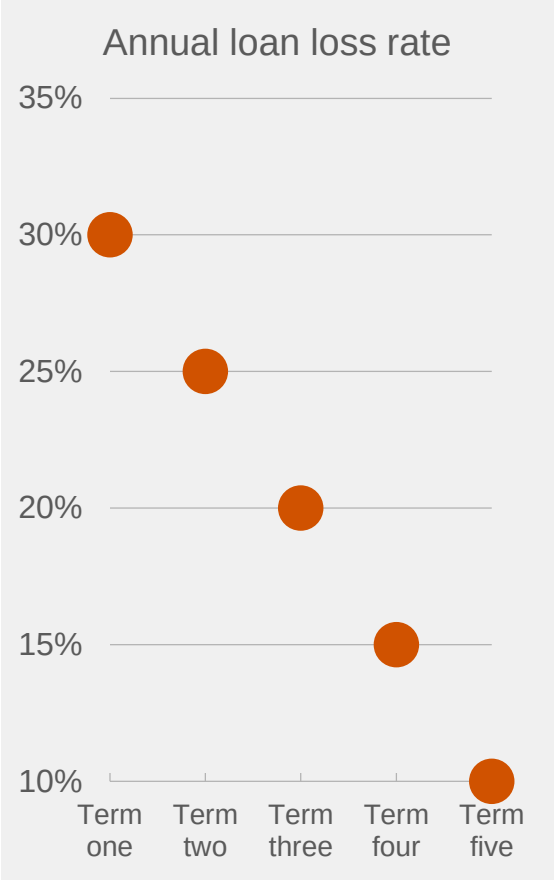


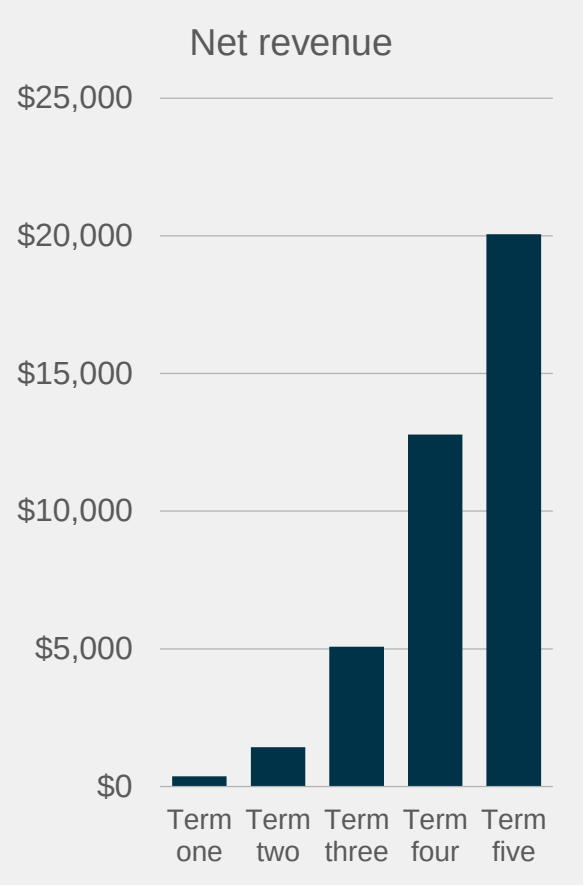
Note: The following graphs present a simplified illustration of how a loan portfolio may evolve over time; the numbers depicted are purely exemplary and made up.

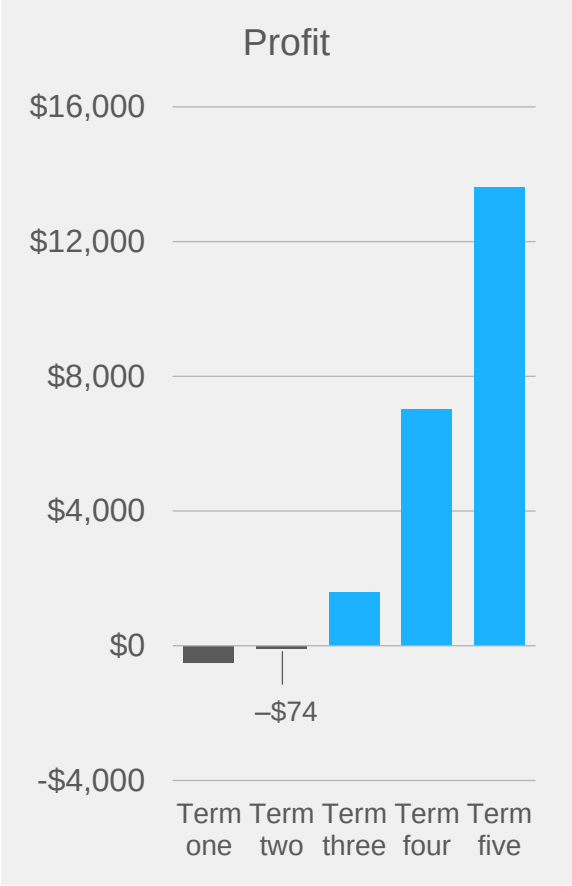
A Financial Model: Portfolio Evolution

At the same time, as you optimize your scoring algorithm, your annual loan loss rate will decline, translating into higher revenues and profit.

Illustrative



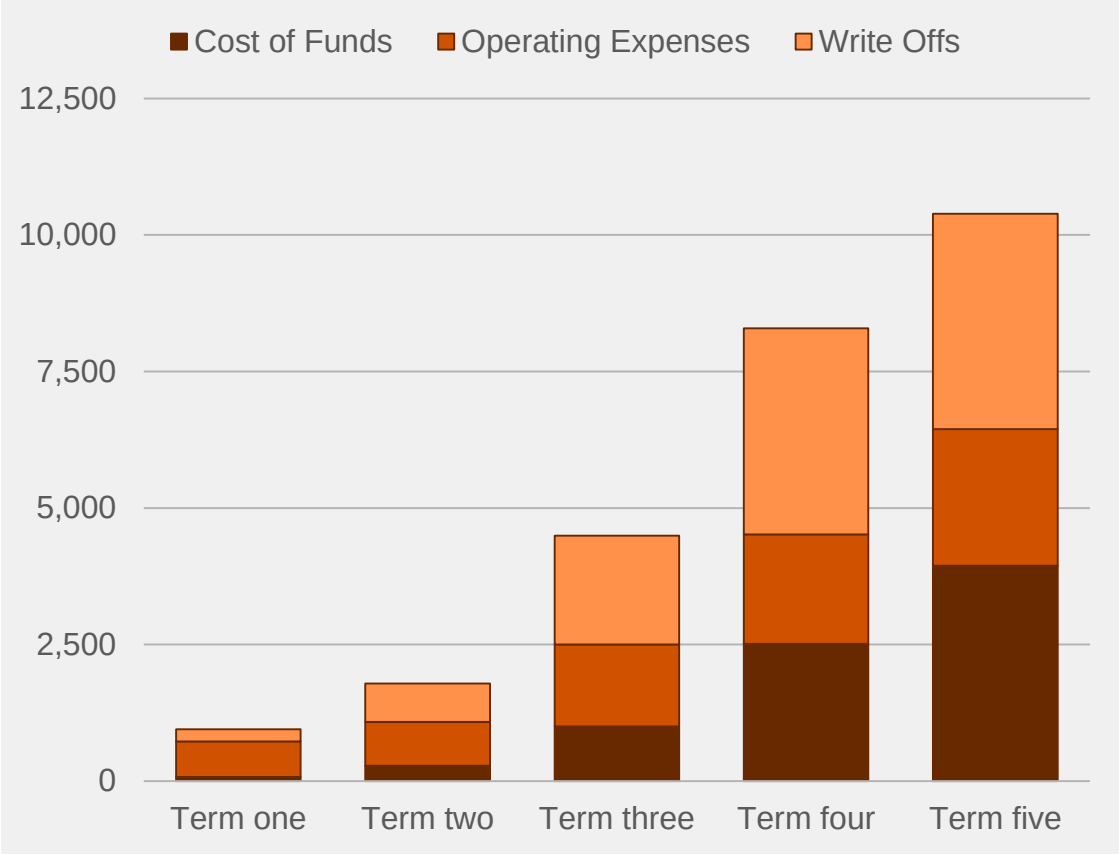


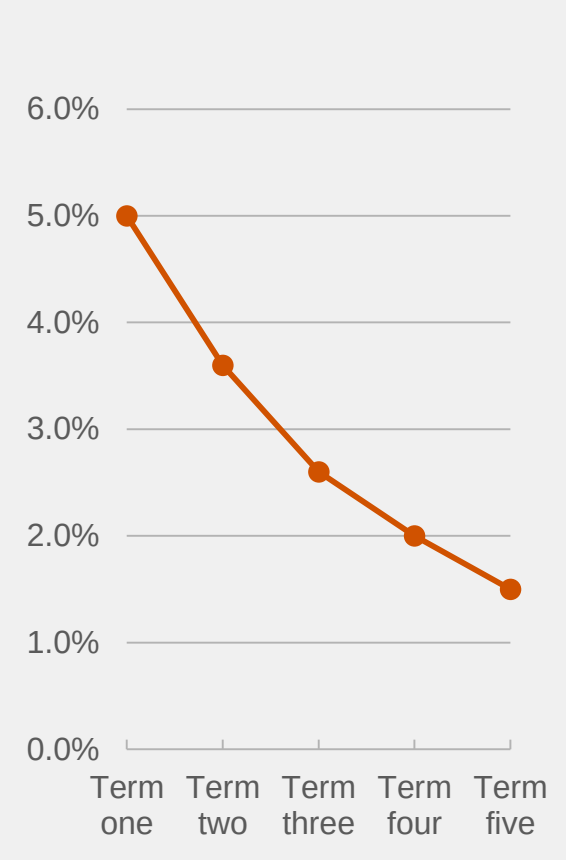


A Financial Model: Portfolio Evolution

Your break-even interest rate will also decrease as your portfolio matures.

Illustrative





Financial Considerations: Summary Points

- Digital credit often involves **small loans repaid quickly, requiring less capital for loan portfolio**;
- Costs are **initially high** due to small loan sizes and higher loan losses;
- It is possible that as a deployment scales, customers increase and loan sizes grow that the **costs fall closer to more conventional lending**;
- Financially, digital credit can be considered several ways: As a **standalone** product, or a **low-cost customer/account acquisition** tool.

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Building Partnerships

PHOTO CREDIT: KM Asad, 2012 CGAP Photo Contest

Partnerships: Key Players and Components

Institutions Involved

Financial Institution

Payment Provider

Communications

Specialty 3RD Party

Key Functions

- Communications
- Payments Instrument
- Cash In/Out Points
- Capital
- Credit Scoring
- Marketing
- Customer Relationship Management
- Collections
- Customer Data

Customer Engagement

Example: Timiza

Communications			airtel	
Payments Instrument		airtel		
Cash In/Out Points			airtel	
Capital	JUMO			
Credit Scoring	JUMO			
Marketing			airtel	
Customer Relationship Management	JUMO		airtel	
Collections	JUMO			
Customer Data	JUMO		airtel	

Example: Alibaba (eCommerce)

Communications			MNOs
Payments Instrument		ALIBABA	
Cash In/Out Points	BANKS		
Capital	ALIBABA		
Credit Scoring			ALIBABA
Marketing			ALIBABA
Customer Relationship Management			ALIBABA
Collections			ALIBABA
Customer Data			ALIBABA

Your Deployment?

- Communications
- Payments Instrument
- Cash In/Out Points
- Capital
- Credit Scoring
- Marketing
- Customer Relationship Management
- Collections
- Customer Data

Building Partnerships: Summary Points

- Most digital credit services **rely on partnerships**, rather than do-it-alone models;
- Partnerships begin with delineating **clear roles,** some of which may be **shared** between partners;
- Partnerships build on **mutually beneficial revenue, risks** and **adjacencies** (sometimes not known at time of pilot).

CGAP

Advancing financial inclusion to improve the lives of the poor

Development Cooperation

Ministry of Foreign Affairs of the Netherlands

IFC International Finance Corporation

Global Affairs Canada

Bill & Melinda Gates foundation

Omidyar Network

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Agency for Development and Cooperation SDC

MetLife Foundation
Ensuring Access. Empowering Communities.

Michael & Susan Dell Foundation

The Government of the Grand Duchy of Luxembourg

FMO Entrepreneurial Development Bank

Ministerio de Asuntos Exteriores y de Cooperación

aecid

UNDP

afd Agence Française de Développement

ILO

USAID From the American People

UKaid from the British people

giz

Federal Ministry for Economic Cooperation and Development

KFW Bank aus Verantwortung

Sida

African Development Bank

Australian AID

Citi Foundation

citi

IFAD Investing in rural people

Ford Foundation

Norad

World Bank Group

UNCDF Microfinance • Capital Development

Repubblica Italiana

IDB Inter-American Development Bank

The MasterCard Foundation

Multilateral Investment Fund Member of the IDB Group

ADB

European Investment Bank

www.cgap.org