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How do they pay as they go?: Learning payment patterns from solar home system users data in Rwanda and Kenya

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A R T I C L E I N F O

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A B S T R A C T

Pay-as-you-go (PAYGo) financing models play a vital role in boosting the distribution of solar-home-systems (SHSs) to electrify rural Sub-Saharan Africa. This financing model improves the affordability of SHSs by supporting the payment flexibility required in these contexts. Such flexibility comes at a cost, and yet the assumptions that guide the PAYGo model design remain largely untested. To close the gap, this paper proposes a methodology based on unsupervised machine learning algorithms to analyse the payment records of over 32,000 Rwandan and 25,000 Kenyan SHS users from Bboxx Ltd., and in so doing gain detailed insights into users' payment behavioural patterns. More precisely, the method first applies three clustering algorithms to automatically learn the main payment behavioural groups in each country separately; it then determines the preferred customer segmentation through a validation procedure which combines quantitative and qualitative insights. The results highlight six behavioural groups in Rwanda and four in Kenya; however, several parallels can be made between the two country profiles. These groups highlight the diversity of payment patterns found in the PAYGo model. Further analysis of their payment performance suggests that a one-size-fits-all approach leads to inefficiencies and that tailored plans should be considered to effectively cater to all SHS users.

Introduction

Access to reliable modern energy sources is vital for human development and prosperity (Valickova & Elms, 2021). In line with this, the United Nations have set a target of universal energy access by 2030 in the seventh Sustainable Development Goal (SDG 7) (UN GA, 2015). However, it is anticipated that 620 million people will remain without access by (UNECE, 2020). Sub-Saharan Africa (SSA) is the most affected region with 540 million people without access to electricity and no reduction in absolute terms is now expected by 2030, in part due to the economic impacts of COVID-19 (IEA, n.d.). On top of this, there is a significant urban-rural access divide which aggregate electrification rates overlook. SSA urban access rates reached 77 % in 2018, whereas rural access remained at 27 % on average (UNECE, 2020). Hence, rural electrification efforts are still central to achieve universal access since, despite the unprecedented urbanization rates witnessed in the region, 60 % of SSA population still resides in rural areas (IEA, 2019).

Stand-alone off-grid solutions, in particular Solar Home Systems (SHSs), have proven to be the most cost-effective electrification solution in remote rural areas with challenging topographies, limited affordability, and low demand (Bisaga et al., 2021). These systems, comprised of a battery pack and a solar PV panel typically ranging from 11 to 100 watts capacity, represent a quickly deployable solution which can provide basic energy services (IEA, 2019). Despite their limited capacity, a meta-analysis on the household impact of SHS has found consistent positive correlations with improved education, household income, employment rates, time uses, and women empowerment (Urgessa Ayana et al., 2022). In recognition of this, SHSs have been given a central role in several electrification plans. In a fully electrified Africa by 2030 scenario, the International Energy Agency (IEA) estimates that more than three quarters of the rural population (i.e., 450 million people) should gain access through SHSs (IEA, 2019). Both Kenya (Power Africa, 2019) and Rwanda have committed to the technology, with the latter expecting SHSs to reach 38 % of its unelectrified population (GoR,

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2019).

Despite their cost-effectiveness, the upfront cost of SHSs is still prohibitive for large portions of the target population, primarily for remote rural consumers on low incomes. In response to this, flexible payment plans – i.e., Pay-As-You-Go (PAYGo) schemes – emerged at the start of the last decade, wherein only 10–20 % of the unit's cost is paid upfront and the remainder is paid incrementally in a flexible manner (Sotiriou et al., 2018). This financial mechanism has made SHSs affordable to a population 40 % larger than otherwise (GOGLA, 2020), and it is now responsible for 90 % of new units installed worldwide (GOGLA, 2022a), compared to 33 % in 2018 (GOGLA, 2018; EnDev, 2019). In addition, PAYGo schemes are best applied when deployed along with digital payment services and smart SHSs,[1] both of which have contributed to the accumulation of detailed records of user usage data (Bisaga et al., 2017). Considering that SHSs are often deployed in previously data scarce locations (Glassman & Ezeh, 2014), these devices are contributing to a leapfrog in user data availability.

These real time energy and payment records could be of great benefit to support electrification efforts (Bisaga et al., 2017), as well as to help monitor and improve how digital finance will continue to shape the off-grid solar sector (Waldron et al., 2021). Nevertheless, our analysis shows a paucity of literature on data analysis and evaluation of PAYGo models for SHS at scale. This has led to a scenario in which many of the assumptions which sustain the payment model have yet to be verified; thus, leading to a potentially inefficient use of resources. A key element of the PAYGo model relates to how payment flexibility is provided. This requires an understanding of the users' needs and behaviours; however, little empirical research has been carried out to verify whether the current model design is well suited to all the users it is intended to serve. Therefore, given the ambition of SDG7 and the scale PAYGo SHSs have reached, there should be continued efforts to ensure that resources are being used as efficiently as possible.

The present study contributes to this goal by analysing the payment behavioural diversity found in PAYGo users and assessing whether the current PAYGo model design caters to all the user types it serves. For this, the study uses unsupervised machine learning algorithms to analyse a large dataset of PAYGo SHS users, containing over 38,000 Rwandan and 29,000 Kenyan Bboxx Ltd. customers. Users are characterized according to their PAYGo transaction logs, which are synthesized into a set of five aggregate features designed to capture the most relevant behavioural aspects. Three clustering algorithms are then used to automatically learn the main user types in each country separately. Finally, the respective preferred customer segmentations are identified through a combined quantitative and qualitative validation procedure to ensure their contextual analytical value. This approach identifies a spectrum of payment behaviours which, through an analysis of their payment performance, also reveals inefficiencies in the current PAYGo model design.

Background

Presently, the responsibility of providing basic energy services to rural and poorer areas of SSA falls largely on for-profit private organizations. Of these, there is a subset of large companies, founded and operated in the Global North, that receive most of the attention from international organizations and funding bodies in return for generating the market-led solutions entrusted to fulfil electrification agendas (Groenewoudt & Romijn, 2022). Though not without opposition, the shift away from state-own and non-profit initiatives has been gaining momentum since the early 1980s. At the start of the century, the introduction of global development goals had a decisive impact on the privatization of electrification efforts. It spurred large investment interest from agents which favoured for-profit models that, nonetheless, put social and environmental impact first, and profits second. This pressured much of the remaining non-profit institutions to adapt, and brought for-profit enterprises closer to the development agendas, resulting in the organisational environment witnessed today (Groenewoudt & Romijn, 2022). Throughout this process, local governments have generally limited their support of the private sector to tax exemptions on import duty and value added tax on the hardware of the units (Muchunku et al., 2018). Only more recently has support for SHS been explicitly expresses in electrification plans, as exemplified by Rwanda (GoR, 2019) and Kenya (Power Africa, 2019) which has since developed into direct subsidy schemes (GOGLA, 2022a).

Today's large SHS providers rely heavily on the PAYGo model and have leveraged it to expand their SHS operations and beyond (GOGLA, 2022b). The model was developed to support the delivery of off-grid solar energy with a new customer financing scheme catered to populations without access to traditional financing services. It relies on a remote-locking mechanism that ties the energy service with incremental loan payments, which allows PAYGo providers to offer much greater payment flexibility than Microfinance Institutions (MFIs) (Muchunku et al., 2018). Users gain access to SHS after an initial deposit (i.e., 10 %–20 % of the unit's cost), after which they must purchase days of credit to use the unit; in the absence of credit the unit automatically switches-off, but service is reestablished with the purchase of new credits. Payment flexibility is granted both in the timing and amount of each payment, in addition to exempting users from compensating for days without payment; all of which is conceded to cater to irregular income streams (Moreno & Bareisaite, 2015).

While payment flexibility is the model's most desirable feature, it is also its most expensive. By creating uncertainty in revenue streams, flexibility significantly increases the complexity and cost of delivering SHSs (Moreno & Bareisaite, 2015). As such, there are limits to how much payment flexibility distributers can accommodate. Most opt to impose an expected completion period, typically ranging from six months to three years (Muchunku et al., 2018). This serves to set the daily rate charged to use the SHS, but users are free to pay at their discretion and are allowed to go for short periods without payment, and therefore service. Some providers, however, have additional restrictions such as requiring a minimum number of paid days within a given period (e.g., 25 days in a month), or imposing stricter payment regimes, either through relatively high minimum payment amounts (e.g., at least a week at a time) or fixed payment regimes (i.e., weekly, or monthly) (Moreno & Bareisaite, 2015).

Regardless of the differences, it is inevitable that the PAYGo model adds financial costs to a service where affordability is still the main barrier for adoption (Waldron et al., 2021). Therefore, it is important that the design of the model ensures that the resources devoted to it are used as efficiently as possible. However, many of the assumptions that sustain the model have yet to be tested. There is evidence that most providers do not have an empirical justification for the pricing of the added costs of the financing scheme (Waldron et al., 2021). The upfront deposit remains the main mechanism to assess a new client's ability to pay (Muchunku et al., 2018), despite the lack of evidence to support its effectiveness (GOGLA, 2020). Locking the unit is the main mechanism for payment compliance, but there is no reporting on the efficacy of the technology in improving energy payment performance (Waldron & Swinderen, 2018). Though most crucially for the present analysis, there have been no efforts to verify whether the current modes of payment flexibility are well suited to all those it is intended to serve.

As such, the present study sets out to assess whether the current PAYGo model design, with its one-size-fits-all offering of flexibility benefits, as well as penalties and incentives for compliance, is well suited to the variety of user types it is intended to serve. This because the model design seemingly accommodates a range of lifestyles and their respective payment patterns by allowing users to pay in the amount and

[1] Smart SHSs are equipped with Internet of Things (IoT) capabilities which transmit information in real-time about the device's usage and hardware monitoring parameters.

frequency of their convenience. However, leniency on late payments – i. e., the costliest element of the model – does not seem to reflect such a wide variety of behaviours. It is designed to accommodate sporadic short periods of non-payment (i.e., in the order of days), applying only light penalties for such instances (e.g., minimum late payment fees). This is most beneficial for users that naturally pay in small high-frequency amounts – perhaps reflecting their income streams – where a momentary shortness of funds is rightly not viewed as a wavering ability or willingness to pay. However, if users have other payment behavioural tendencies, then this costly mode of leniency may not be as well suited to their conditions. Therefore, while the PAYGo model succeeded in making SHSs more affordable for many, its current one-size-fits-all approach may be hindering a more efficient deployment of SHSs.

Literature review

The need to improve our understanding of SHS user behaviours has been previously recognized in the literature (Bisaga & Parikh, 2018). Simultaneously, data-driven methods have also been recognized as necessary elements in this research context to provide the empirical insights needed to optimize resource allocation (Dominguez et al., 2021). However, an exhaustive literature review has found that only 31 % of 139 studies dedicated to SHSs in SSA applied quantitative methods, which was conjectured to resulted from lack of access to user usage data (Kizilcec & Parikh, 2020). Indeed, the present analysis confirms that there is a paucity of academic literature leveraging large scale datasets to understand customer payment payments for SHS (See Table 1).

Not all studies listed in Table 1 leveraged their data resources to investigate payment behavioural patterns. In (Barry & Creti, 2020), the authors assess the fitness of the PAYGo model to reach 'last mile' users in Benin; their findings revealed that most users were in urban grid-electrified areas instead. In (Kennedy et al., 2019), the authors leverage a large set of SHS, payment performance, and socio-demographic user characteristics to highlight potential shortcomings in PAYGo customer acquisition strategies. The remaining academic studies do find empirical insights on PAYGo user behaviour and model performance; however, their limited number reflects the paucity of research in this context. Whereas the two industry led efforts (Jain et al., 2020; Khaki et al., 2021) highlight the existence of significant data resources, but also fall short of making significant contributions to our understanding of user payment behaviours.

In (Barrie & Cruickshank, 2017), although the analysis focuses on the PAYGo model's ability to reach 'last mile' users, it also highlights a mismatch between the model's design and its users' reality. It shows that some of the top reasons for default were seasonal incomes (e.g., from agriculture or tourism) and extended job-related travel. This because, despite being common circumstances in the context, these conditions resulted in frictions with the expectation of constant high frequency recurrent payments.

Table 1
Data-driven studies assessing the PAYGo model.

Studies	Unit Type	Sample size	Data type[a]	Sampled time window
(Kennedy et al., 2019)	SHS	68,600	PH, SD	1.5 years [562 days]
(Barry & Creti, 2020)	Pico-solar; SHS	8845; 1275	PH, SD	3 years [40 months]
(Guajardo, 2021)	Pico-solar	1832	PH	6 months
(Barrie & Cruickshank, 2017)	SHS	1376	PH, FS	1 year [392 days]
(Guajardo, 2019)	Pico-solar	882	PH, EC	6 months
(Jain et al., 2020)	SHS	672,236	PH, FS	2 years [26 months]
(Khaki et al., 2021)	SHS	450,000	PH	6 months

[a] PH: Payment History records (i.e., Time-series), SD: Socio-Demographic data, EC: Energy Consumption data (i.e., Time-series), FS: Field Survey data.

To date, the most direct insights on PAYGo user behaviour are given by the two remaining studies of the same authorship - albeit applied to the smaller pico-solar[2] devices (Guajardo, 2021; Guajardo, 2019). In the first (Guajardo, 2019), the author demonstrates a link between user payment and energy consumption patterns. It showed that, on average, energy consumption decreased in the week prior to a missed payment, and that early energy consumption patterns were a good predictor of default. In the second (Guajardo, 2021), through a descriptive analysis, the author provides the first assessment of observed payment behavioural patterns. It highlights an ample use of payment flexibility, where over 70 % of users paid in less consistent and in larger amounts than expected. Nevertheless, it also found evidence of two broad behavioural groups, where most users roughly followed either a weekly or a monthly regime. Moreover, these groups displayed different payment performances, where weekly payers repaid their loans faster, despite their less predictable behaviour. The study revealed the existence of different behavioural patterns, each having different degrees of compatibility with the PAYGo model.

The two industry led efforts (Jain et al., 2020; Khaki et al., 2021) demonstrate how institutions are leveraging PAYGo data resources for the benefit of the wider sector. In (Khaki et al., 2021) these were used to exemplify the predictive power of new key performance indicators, where early payment behaviour was found to be a good predictor of user performance. In (Jain et al., 2020), a detailed geographical analysis – with access to 75 % of the Ugandan mobile money market – supported the creation of a platform to optimize the deployment of SHSs in the country by commercial distributors. Given its scope, however, the report does not evaluate user payment patterns, instead it only postulates that seasonal earners may be misrepresented by the current PAYGo design.

These initial findings reinforce the premise that there may be inefficiencies in the PAYGo model linked to the behavioural diversity it encompasses. However, the methods used so far are not well suited for an analysis on payment behavioural patterns on a larger-scale dataset. In (Kennedy et al., 2019), the authors demonstrate that machine learning clustering algorithms were better suited to the context than a linear regression analysis; in so doing, they were able to identify nuanced insights, for instance, of implicit socio-economic brackets – i.e., higher and lower income earning farmers. However, despite the growing data resources and the proven suitability of these methods, data-driven tools of similar potential have not yet been leveraged to improve our understanding of PAYGo user behaviours.

Data

Bboxx PAYGo

Bboxx operates across eleven SSA countries and their main commercial activity focuses on the distribution of solar home systems sold via a pay-as-you-go financing model. Their systems are modular and can go from 20-watt up to 300-watt capacity units; however, the bulk of distributed units are in the 50-watt range, varying mostly in the different combinations of appliances bundled with the system. Bboxx operates with a hybrid rent-to-own and fee-for-service model, where customers obtain ownership of the appliances after a three-year period, while the SHSs remain the company's property which charges users a 'energy service fee' for continued maintenance and servicing.

Bboxx's customers thus go through a three-stage PAYGo model. In the first and shortest stage, users pay the unit's upfront deposit which grants them 30-days equivalent of usage. The second stage is the core period of the model, where users repay their loan incrementally in exchange for continued energy services. During this phase, users pre-purchase time-credits to access the SHS, without which the unit is

[2] Pico-solar refers to systems smaller than SHSs (i.e., <11-watt capacity), which often offer only lighting and mobile phone charging capabilities.

automatically and remotely locked. The price of the time-credits is proportional to the cost of the SHS and bundled appliances, resulting in a Daily Rate scheduled to last 3 years. Lastly, once the loan is settled, a lower daily rate is charged for the continued maintenance and support services.

Bboxx provides payment flexibility in-line with most PAYGo providers. It allows users to pay at their discretion, choosing the amount and timing of each payment, so long as a positive credit balance is maintained. Where Bboxx may differ from other providers is in their handling of non-payment, where a minimum payment amount is imposed, forcing users to pay for at least 7 days to unlock the unit.

Resources & data cleaning

The present study focuses on long-term user behavioural patterns during periods of relative normality. Therefore, only records prior to the COVID-19 crisis are analysed (i.e., before April 1st 2020) to avoid the behavioural biases and anomalies that the pandemic is expected to have induced. Furthermore, only users with at least one year of activity prior to the onset of the COVID-19 crisis were included, to ensure the observed patterns reflect established behaviours. Given the above constraints, we chose to focus the present study on Rwanda and Kenya, since these contain both the largest and most long-standing Bboxx customer base with comparable sizes. Their records capture the payment patterns of 38,548 Rwandan and 29,732 Kenyan users, which according to GOGLA's estimates could have represented over 80 % of Rwandan SHS users at the time, and about 4 % of Kenyan SHS users (GOGLA, 2020). On average, each user record contains 2 years of daily activity, starting from when they acquired the SHS, up to the 1st of April 2020 – although for 17 % of users this period corresponds to >3 years (due to delays in repaying the loan).

Each user's payment records are captured by two complementary time-series records: the time-credit balance history and the log of each payment date and amount - both on a daily resolution. For the present analysis, each user's time-series records were transformed into a set of five aggregate features. However, prior to deriving the latter, it was first necessary to implement three data cleaning rules. First, the records pertaining to the upfront deposit period (i.e., first stage of the PAYGo customer journey) were removed, since this is a short transient state where no recurrent payments are expected. Second, records following a default or period of inactivity longer than 120 days were removed; this is because the present study is not aiming to capture such extreme instances of arrears, and if kept these records could skew some of our chosen features. The third and final rule guarantees that all customer records still contain at least five payment instances to ensure that a minimum number of user actions are captured. Table 2 lists the impact of the data cleaning rules on the sample size, both in terms of user numbers and the average length of records.

As Table 2 shows, removing the upfront deposit period had only a marginal effect on the user records sample size and average length. On the other hand, the significant reduction in the average record length induced by the second rule, and the subsequent removal of a noticeable number of users with rule three, reveals that there was a meaningful

Table 2
Data cleaning steps.

Country		Original	Rule 1	Rule 2	Rule 3
Rwanda	N° users	38,548	−0 %	−1 %	35,850 (−7 %)
	Days in record[a]	740	−2 %	−14 %	674 (−9 %)
Kenya	N° users	29,732	−0 %	−1 %	27,948 (−6 %)
	Days in record[a]	711	−3 %	−17 %	619 (−13 %)

Notes: The percentages (%) represent the accumulative reduction relative to the original sample size.

[a] Days in record reflects the average number of days in the individual transaction logs.

share of users with almost no normal activity on record. These are likely to represent cases where the introduction of a PAYGo SHS was not successful, and thus fall out of the scope of the present study.

Methodology

To analyse the diversity of PAYGo SHS user payment patterns, the present study implements a three-step approach that converts the raw individual transaction logs into an interpretable customer segmentation for each country's user sample. These steps can be broadly described as follows:

i) **Feature Engineering:** Each user's individual time-series records were converted into a set of five aggregate features designed to synthesize the main behavioural aspects embedded in the records and thus improve interpretability. Some of these features are part of the original contribution of the present study while others have been adopted from recent industrial guidelines (Khaki et al., 2021) to further improve the contextual relevance of the results.

ii) **Clustering:** The behavioural features are then processed by clustering algorithms to automatically learn the similarity patterns and identify the main user groups. This class of algorithms has been previously applied in the context (Kennedy et al., 2019); the present study goes a step further, by applying three different clustering algorithms to significantly reduce algorithmic bias and add robustness to the results (Xu & Wunsch, 2009). Each algorithm produces seven solutions – varying the predefined number of clusters (i.e., **k**) from 3 to 9 - resulting in a total of twenty-one customer segmentation solutions per country.

iii) **Validation:** The final step serves to prune and select the most relevant customer segmentation solution from each country, to be subject to further analysis. This is achieved through a validation strategy adapted from (Sause et al., 2012; Nguyen et al., 2018), which combines a quantitative approach with qualitative oversight, to facilitate an efficient context-centred evaluation of the clustering results.

Feature engineering

In the first step of the methodology both the individual payment transaction logs and the time-credit balance history time-series records were used to derive the five aggregate features which help to synthesize key elements of user payment patterns. Although correlated, payment history catalogues user-initiated actions, while time-credit serves to guide company actions (e.g., SHS lockouts) and may occasionally be influenced by other factors besides payments (e.g., promotional campaigns); therefore, both are needed to record and contextualize user interactions with the PAYGo model. The payment records were normalized by their respective daily rates, converting their monetary value into days of credit equivalent. This transformation has allowed for the direct comparison between users with differently sized SHSs and between Rwandan and Kenyan users. Table 3 summarises the five aggregate features chosen:

These features aim to capture tangible aspects of user interactions with the PAYGo model and characterize each individual user according to these five dimensions. The first two, *Pay* and *std*(*Pay*), serve to capture the preferred payment regime. In Bboxx's case this is only reflected by on-time payments, since the minimum 7-day payment fee imposed on late payments skews the user's voluntary preference. The other three features help to define how customers use the existing PAYGo late payment flexibility. *PLP* shows how often a user is late on payments, while the *CDU* features, adapted from (Khaki et al., 2021), describe the duration of these late periods.

In addition to the three data cleaning rules, an outlier policy was also implemented after the five aggregate features were engineered. Most of

Table 3
Payment behavioural features.

Name	Acronym	Description
Payment size	*Pay*	Preferred relative payment size – when on-time - defined by the equivalent average days of credit purchased.
Payment variability	*std*(*Pay*)	Measure of consistency of on-time payment size, given by the standard deviation of *Pay*.
Percentage of late payments	*PLP*	Relative frequency of arrears periods, given by the ratio of number of late payments over the total number of payments.
Average consecutive days unpaid	*A-CDU*	Typical duration of arrears periods defined as the average length of periods spent without time-credits.
Maximum consecutive days unpaid	*M-CDU*	Longest period spent in arrears, captured by the maximum length of all periods without time-credits.

the feature distributions were heavily right-tailed, which had a significant impact on the performance of the clustering algorithms. Therefore, an outlier policy was implemented where values greater than the 98 % quantile – of the respective distributions - were removed. This resulted in the final sample size used in the analysis containing 32,151 Rwandan users, with an average 690 days in record, and 25,291 Kenyan users with an average 635 days in record. Table 4 provides statistical information of each feature, namely the range, average, standard deviation, and shape of their distributions for each country's final sample:

Clustering algorithms

The unsupervised nature of clustering algorithms allows them to learn patterns of similarity with no contextual information; however, this implies that each algorithm operates under a different definition of an optimal cluster (Hennig, 2015a), which may not suit a given context. To alleviate this effect, three clustering algorithms are implemented, with so exploring different biases and ensuring a more suitable fit. In addition, when conducting a customer segmentation, it is preferable to prioritise cluster homogeneity over separability – i.e., preferring clusters composed of similar users rather than guarantying clear cluster boundaries (Hennig, 2015a). Considering this preference, the following three algorithms were selected: the k-Means algorithm (MacQueen, 1967), the Hierarchical Clustering algorithm with Ward-linkage (HC-ward) (Ward, 1963), and Spectral Clustering algorithm (Shi & Malik, 2000).

The first algorithm, k-Means, intuitively defines clusters based on the distance between datapoints. Through an iterative process, the algorithm defines clusters by their centroids and assigns all datapoints to their closest cluster (Aggarwal, 2015). The Hierarchical Clustering algorithm with Ward-linkage uses a similar distance-based mechanism to define similarity but, unlike the former, it does not rely on an iterative adjustment of cluster boundaries. Instead, the HC-ward algorithm progressively merges similar groups of datapoints from the bottom up, ultimately defining a tree-like structure which maps similarity at an increasingly broader scale (Reddy & Vinzamuri, 2014). Due to their reliance on Euclidean distance, both algorithms impose a strong bias towards forming spherical clusters, regardless of the underlying data structure (Aggarwal, 2015). To counter this, the Spectral Clustering algorithm was also included, given its ability to identify clusters of arbitrary shapes. It achieves this by defining a similarity graph (i.e., presently via the k-Nearest Neighbour algorithm) upon which it derives a series of transformations to facilitate the application of a classic clustering algorithm (e.g., k-Means) to then find clusters without a shape bias (Liu & Han, 2014). All three algorithms require the number of clusters (i.e., **k**) to be predefined, which we presently vary between 3 and 9, inclusive, to derive a total of 21 clustering solutions per country. All algorithms were implemented using the Scikit-Learn Python Library (Pedregosa et al., 2011) with otherwise all the standard parameters.

Validation methodology

A typical approach to identify the preferred clustering solution is to rely on a single Clustering Validation Index (CVI); however, like clustering algorithms, these indices have implicit optimal cluster definitions which may not suit the present context (Akhanli & Hennig, 2020). Ultimately, a qualitative assessment of each solution's suitability to the context would be desirable, but this is impractical given the number of solutions. Therefore, a two-step validation approach was implemented, where the first step prunes the number of desirable solutions through a quantitative approach, and the second step identifies an optimal final solution based on its qualitative interpretable value.

The first step attenuates the bias of each individual index by combining four different CVIs into an ensemble ranking system similar to those in (Sause et al., 2012; Nguyen et al., 2018). Each index ranks all

Table 4
Payment behavioural features.

Feature	Units	Country	[Min, Max]	Average	Stand. dev.	Distribution*
Payment size	[Days]	Rwanda	[0.22, 35.63]	10.04	7.90	
Pay		Kenya	[0.05, 35.56]	5.65	5.71	
Payment variability	[Days]	Rwanda	[0, 21.47]	5.03	4.05	
std(*Pay*)		Kenya	[0, 21.48]	3.83	3.73	
Percentage of late payments	[Days]	Rwanda	[2.08, 97.19]	49.54	22.16	
PLP		Kenya	[1.83, 97.2]	62.67	22.51	
Average consecutive days unpaid	[%]	Rwanda	[0, 40.25]	9.84	7.02	
A-CDU		Kenya	[0, 40.29]	9.75	6.55	
Maximum consecutive days unpaid	[Days]	Rwanda	[0, 120]	43.35	27.25	
M-CDU		Kenya	[0, 120]	42.16	27.39	

Disclaimer: *The variable plots in the *Distribution* column serve only to illustrate the shape of the respective distributions; they do not share the same axes or scale. Note that all features were rescaled to a [0, 1] scale prior to implementing the clustering algorithms, since some of these algorithms are sensitive to the features' scales.

solutions from best to worst, assigning 21 points to the first and 1 to the worst; after this, the final ranking of the ensemble is given by the overall sum of points. The top four solutions are then evaluated in the second step, with additional quantitative insights given through the individual CVI votes, which reveal the level of consensus and potential biased preferences.

Both the Davies-Bouldin (DB) index (Davies & Bouldin, 1979) and the Silhouette (Sil) index (Rousseeuw, 1987) were included in the ensemble due to their popularity in the literature and their benchmarked performance (Arbelaitz et al., 2012). However, it is also known that the DB index has weak affinity towards the k-Means algorithm and the Sil index prefers solutions with fewer clusters (Hennig, 2015b); most importantly, both indices have a bias towards spherical cluster solutions (Akhanli & Hennig, 2020). To counter this, the S_Dbw index (Halkidi & Vazirgiannis, 2001) and the Clustering Validation index based on Nearest Neighbours (CVNN) (Liu et al., 2013) were included, since both should not be afflicted by the spherical bias (Liu et al., 2013). The implementation of the first two indices was done through the Scikit-Learn Python Library (Pedregosa et al., 2011) with all the standard parameters; while the S_Dbw and CVNN indices were implemented using the clusterCrit (Desgraupes, 2018) and fcp (Hennig, 2020) R language libraries, respectively, also with all the standard parameters.

Results

See Tables 5 and 6 for the top four solutions of the ensemble validation approach for Rwanda and Kenya, respectively. In either case, no more than two CVIs agreed on the preferred solution and no top one choice of any index had a total rank >3. This disparity between indices demonstrates how a reliance on a single CVI would have been misleading and highlights the need for a contextual qualitative value assessment. Where the ensemble method does agree is on the underperformance of the HC-ward algorithm - which only achieved a maximum rank of 8 in Rwanda and 7 in Kenya - and was thus disregarded from further comparisons.

In the Rwandan case (Table 5), we find that the top one rank is shared by three solutions, one from the Spectral Clustering algorithm and two from the k-Means algorithm, which also produced the rank 2 solution. Between these top four solutions, those from the k-Means algorithm emerge with a less harmonized consensus, whereas the Spectral Clustering solution received a more moderate but also more consistent scoring across indices.

The interpretable value of these solutions is influenced both by their ability to identify sufficiently diverse behavioural groups, and by how well-delineated these groups are. In this regard, the k-Means (k = 3) solution was discarded since it does not reveal a level of behavioural diversity comparable to its top-ranking peers. The k-Means (k = 4) solution does provide enough diversity, however it fails to effectively delineate contextually important payment regimes (i.e., defined through the *Pay* and *std*(*Pay*) features) which the remaining two solutions do. The k-Means (k = 5) and Spectral Clustering (k = 6) solutions identify very similar profiles, where each cluster of the first has a parallel in the second. However, the additional cluster identified by the Spectral Clustering (k = 6) solution provides further detail on the monthly payment regime followers, which was found to be decisive for the subsequent discussion. Therefore, the Spectral Clustering solution was selected for further analysis.

Table 5
Rwanda CVI ensemble ranking.

Clustering algorithm	Rank	Total votes	*Sil*	*DB*	*S_Dbw*	CVNN
Spect.Clust. ($k = 6$)	1	58	13	16	14	15
k-Means ($k = 4$)	1	58	16	8	15	19
k-Means ($k = 3$)	1	58	15	9	20	14
k-Means ($k = 5$)	2	57	20	17	11	9
…	…					…
HC-ward ($k = 3$)	8	45	12	1	19	13

Table 6
Kenya CVI ensemble ranking.

Clustering algorithm	Rank	Total votes	*Sil*	*DB*	*S_Dbw*	CVNN
k-Means ($k = 3$)	1	69	19	14	20	16
k-Means ($k = 4$)	2	62	20	12	17	13
Spect.Clust. ($k = 4$)	2	62	13	16	19	14
Spect.Clust. ($k = 3$)	3	59	2	15	21	21
…	…					…
HC-ward ($k = 4$)	7	46	7	4	16	19

From Table 6, we observe that in the Kenyan case solutions with fewer clusters were preferred. Unlike the previous case, the rank one solution has a significant lead over the top four. Nevertheless, the remaining top solutions still stand out because of their high total scores, which are greater than any Rwandan top four solution. Although the Spectral Clustering (k = 3) solution was the preferred choice of two CVIs simultaneously, it was also heavily penalized by the *Sil* index and was thus discarded. The other top three solutions benefited from a more balanced vote, and we thus looked into each of these for qualitative assessment.

Although the k-Means (k = 3) solution was the preferred CVI choice, it also has the least interpretable value of the four. Unlike all others, it fails to differentiate monthly regime followers; this might be due to the fact that this segment is less numerous in Kenya (as discussed below), and the k-Means algorithm tends to generate more evenly-sized clusters (Akhanli & Hennig, 2020). Indeed, both Spectral Clustering solutions clearly identified this segment. We then qualitatively compared k-Means (k = 4) and Spectral Clustering (k = 4) solutions. Although they highlight similar profiles with one-to-one parallels, we found Spectral Clustering (k = 4) was more capable of separating subgroups, especially for the large weekly regime segment; for this reason, the Spectral Clustering (k = 4) was selected.

Discussion

Customer segmentation

The preferred customer segmentation solutions for Rwanda and Kenya are displayed in Figs. 1 and 2 respectively, where the clusters are visually represented by the distribution of each aggregate feature for their respective customer sample. All features are represented in a [0, 1] range – in accordance with the clustering procedure – and each is assigned a colour as labelled in the legends of Figs. 1 and 2. We observed that most clusters have well-defined preferred payment routines, falling into either a weekly or monthly regime – as reported in (Guajardo, 2021). Beyond these, clusters are also identifiable by how they incur into late payment periods, where the three relevant features (i.e., *PLP*, *A-CDU*, and *M-CDU*) allow to differentiate between the frequency and duration of these periods. By combining these two aspects it is possible to characterize each Rwandan cluster as follows:

Cluster R1 – Weekly On-time: With an average payment size of 6.2 days and a mode of 7 days, this cluster constitutes the first Rwandan cluster with customers that prefer to follow a weekly payment regime. In addition, all late period features are relatively low in relation to the other Rwandan clusters, which is why these users are labelled as *on-time*.

Cluster R2 – Weekly High PLP: Having a slightly lower average *Pay* of 4.5 days, but a mode still of 7 days, this cluster captures the second group that follows a weekly payment regime. The distinguishing feature of this segment is their consistently higher frequency of incursion into late periods – i.e., their *PLP* values. Unlike other segments, at least 50 % of payments are late for all its users; while the majority (i.e., >75 %) has a *PLP* value higher than every other cluster's average.

Cluster R3 – Weekly High CDU: This is the last Rwandan cluster to

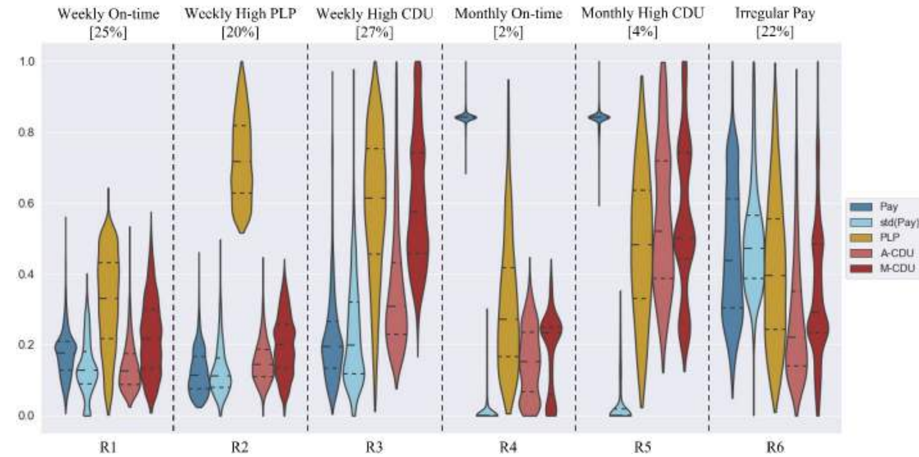

Fig. 1. Rwandan customer segmentation. The top displays the general description and relative share of each cluster, while the bottom assigns the cluster names.

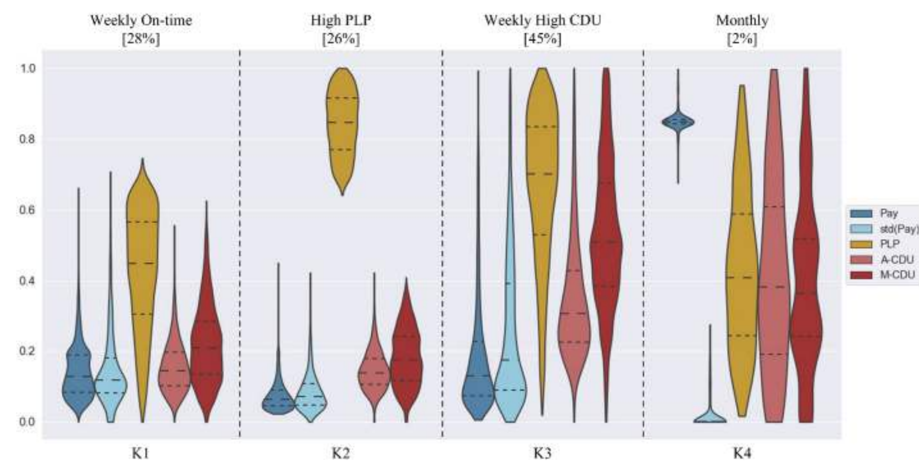

Fig. 2. Kenyan Customer Segmentation. The top displays the general description and relative share of each cluster, while the bottom assigns the cluster names.

follow a weekly regime as it has an average *Pay* of 7.8 days and still a mode of 7 days. This cluster is best characterized by the long periods in arrears relative to the other weekly regime clusters. At 14.3 days, the average *A-CDU* of cluster R3 is more than twice that of its weekly counter parts - i.e., R1 and R2; while its average *M-CDU* is over 72 days longer than the latter's extreme values.

Cluster R4 – Monthly On-time: The first monthly payers' cluster captures a segment of very consistent regime-following users. Over 50 % of its users prefer a payment size of 30 days and on average the cluster has the lowest payment variability at 0.3 days. On the other hand, while its *PLP* values may have a wide range, their average - at 31.5 % - is the lowest of all six clusters. In addition, both *CDU* values are among the lowest with averages at 6.2 days and 21.7 days for *A-CDU* and *M-CDU*, respectively.

Cluster R5 – Monthly High CDU: The second and last segment of Rwandan monthly payers once more captures steady regime followers, albeit with a payment variability marginally larger at 0.7 days, but with a *Pay* majority still firmly at 30 days. Contrary to their monthly peers (i.e., R4), this segment contains users that tend to be in arrears for long periods at a time, with average *CDU* values at 22.3 days and 66.7 days for *A-CDU* and *M-CDU*, respectively.

Cluster R6 – Irregular Pay: Lastly, the final segment contains the "exception to the rule", where it cannot be said that most customers follow either a monthly or weekly regime. Instead, this cluster is characterized by the highest payment variability averaging on 10.6 days. Although values range greatly within the cluster, this group also appears to fall into arrears more often and for longer than most, with an average *PLP* of 41.1 % and an average *M-CDU* of 41.6 days.

The Kenyan customer segments are illustrated and characterized in Fig. 2, which facilitates a similar characterization:

Cluster K1 – Weekly On-time: Captures the first Kenyan group of weekly payers, which share a similar profile to their Rwandan cluster R1 counterparts. In line with the latter, this segment has an average *Pay* of 5.1 days, but a mode of 7 days; tends to be late on payment less often and to remain so for shorter periods, with an average *PLP* of 42.4 % and an average *A-CDU* of 6.3 days.

Cluster K2 – High PLP: With an average *Pay* of just 2.7 days, and a variability of 1.9 days, this segment has the highest preferred payment frequency of all clusters in both countries (indeed, strictly speaking it cannot be described as weekly payers). Nevertheless, it shares similarities with Rwandan cluster R2 of weekly payers, in that *PLP* values are distinctly high, where the minimum value is as high as 63 % and the average is 82.1 %.

Cluster K3 – Weekly High CDU: As the last Kenyan group of weekly payers, this segment also exhibits a similar profile to its Rwandan counterpart, i.e., R3: cluster K3 has a weekly average *Pay* of 6.8 days, and its average CDU values significantly surpass the previous two Kenyan clusters at 13.9 days and 63.6 days, for *A-CDU* and *M-CDU*, respectively.

Cluster K4 – Monthly: In Kenya's case, only one cluster emerges with a monthly regime preference. As with its Rwandan equivalents (i.e., R4 and R5), these users staunchly follow a monthly routine, where payment variability is as low as 0.4 days, and over 50 % of user's *Pay* is set at 30 days. However, unlike the Rwandan case, no differentiation is suggested between on-time monthly payers and otherwise (hence we have a single monthly cluster as opposed to two).

As noted above, most Kenyan segments have a Rwandan counterpart, with two notable exceptions. Firstly, Rwanda's R6 Irregular Pay cluster does not have a Kenyan equivalent. This may be explained by revisiting Table 4 and comparing the Rwandan and Kenyan *std*(*Pay*) distributions. Kenya's *std*(*Pay*), unlike Rwanda's, does not have a meaningful share of midrange values, suggesting that in Kenya it is not as common for users to have a high payment variability. Secondly, no distinction between Kenya's monthly payers was deemed relevant. This may have resulted from the smaller share of Kenyan monthly users relative to Rwanda (see Figs. 1 and 2).

Overall, we find the weekly payment regime to be the most popular in both countries, with a total of 72 % of users in Rwanda and 73 % in Kenya preferring it. Furthermore, cluster K3 alone represents almost half of Kenyan users. Beyond the monthly-weekly regime dichotomy, described in (Guajardo, 2021), we presently find that the exceptions constitute a meaningful share of users. In Kenya's case, cluster K2 suggests that over a quarter of users prefer faster regimes than the latter. Whereas Rwanda's cluster R6 finds that 22 % of users cannot be aggregately grouped into one regime, instead showing that a large share of users followed irregular payment regimes.

User payment performance

The aggregate payment performance of each cluster can help assess the current PAYGo model's ability to accommodate the variety of behavioural patterns observed. From a user's perspective, collective low performance may indicate disproportioned burdens inflicted on particular customer groups; while from the standpoint of a PAYGo SHS provider, poor customer performance is an indicator of inefficiency. Presently, payment performance is defined through three metrics, as described in Table 7:

The metrics in Table 7, Collection Rate and Slow Payer, were adapted from an industry-led effort[3] developing new key performance indicators (KPIs) for the sector. Optimally, CR should be above 80 %; however, because the PAYGo model allows users to remain active while making small and sporadic payments, it is possible for the CR to be much lower. This slow payer behaviour is detrimental both for the users (which are bound to a service they are not benefiting from) and the provider (who is not receiving payments) and is thus an important indicator of performance.

See Table 8 for aggregate values of Collection Rate, Default rates, share of Slow Payers and maturity profiles both at country and cluster level. Maturity profiles indicate the average time between a customer's contract start and last day on record. This serves to further contextualize the payment performance metrics, in particular default rates, because the probability a given user has defaulted is higher the longer they have been active. Therefore, higher default rates should be expected from segments with older maturity profiles (Waldron et al., 2021). The countries' maturity profiles are defined by the share of users in each of the three maturity brackets. The clusters' maturity profiles are defined by the relative difference from their respective country's baseline, highlighting whether a segment is more or less mature than its country's average.

Table 7
Payment performance metrics.

Metric	Description
Defaulted	Usually, a customer is only classified as defaulted after an ad hoc analysis; however, presently a customer is also automatically considered as defaulted after 120 consecutive days without time-credits.[a]
Collection rate (CR)	Captures the share of payments received versus the payments expected, as a percentage, during the full period on record for the user.
Slow payer	A customer is a slow payer if their Collection Rate is below a certain threshold; presently the threshold used is 50 %.

[a] Therefore, the current definition of default is not consistent with Bboxx's policy, and so neither are the figures discussed in this paper.

From Table 8 we find that, in general, Rwanda has a better payment performance than Kenya, with a higher CR, and both lower default rates and share of slow payers; this despite an older maturity profile. Within Rwanda's clusters, however, there are signs of a positive correlation between older maturity profiles and higher default rates – i.e., when comparing clusters of the same payment regime. Cluster R5 has a much higher default rate than their R4 monthly compatriots; similarly, between the weekly clusters R1, R2, and R3, default rates also increase with maturity. Beyond this, the two payment regimes show significantly different payment performance profiles. Monthly payers appear to default at much higher rates, where R4 has only marginally lower default rates than R3 – i.e., the worst weekly cluster. Conversely, however, monthly regime-followers also have the highest CR values, while only R2 as lower rates of slow payers. This contradiction may indicate that the current PAYGo model is not as well suited for monthly regime followers, since these customers default more often even with a better overall performance.

Within the weekly regime followers, we find that R2 has the best payment performance, despite the cluster's distinctively high *PLP* values. Cluster R3 was expectedly a worse performer - given its high *CDU* values and older maturity profile - but cluster R1 was not. With its distinctly on-time user segment, R1 has surprisingly lower CR rates and higher share of slow payers than R2. Evidently, higher PLP values - indeed even exclusively high values - do not necessarily contribute to a lower PAYGo performance.

Outside of the weekly/monthly dichotomy, R6's irregular payers display a payment performance profile closer to monthly payers, albeit with less extreme values. Its CR and slow payer rates are more modest than both R4 and R5s, however, its default rates are also lower - despite a relatively old maturity profile - thus resulting in a desirable payment performance, regardless of its high *PLP* and *CDU* values.

In Kenya's case, the parallels with Rwanda found in the behavioural feature profiles seem to persist through the payment performance profiles. Like R2, Kenya's K2 has the best payment performance of the country. Monthly K4 has both the highest default and CR rates, mirroring Rwanda's monthly clusters. As R3, cluster K3 is the worse weekly performer, with the highest default rates and share of slow payers of the regime. Conversely, Kenya's K1 does differ from R1 with higher default rates relative to its country; however, this may be explained by K1's older maturity profile. These similar results reinforce the findings in Rwanda. Where, once more K2's higher *PLP* values did not imply a worse payment performance. And monthly payers, although a minority, show that their consistently distinct behaviour has significant consequences in their payment performance.

Implications

The existence of multiple behavioural types with different payment performance rates indicates that the one-size-fits-all approach currently guiding PAYGo model design and evaluation may be hindering a more effective distribution of SHSs. Beyond highlighting inefficiencies, the existing results also help to contextualize how the various segments experience the PAYGo model differently and why this may affect their payment performance.

Firstly, the clusters with profiles closest to the daily payment regime

[3] PAYGo PERFORM is part of an ongoing industry-led campaign to standardise KPIs in the off-grid solar sector. It is governed by the CGAP, GOGLA, IFC Lighting Global, and CDC, and was developed in collaborations with hundreds of industry stakeholders.

Table 8
Cluster payment performance.

Cluster	Collection rate	% Defaulters	% Slow payers	Maturity[a]		
				Young	Middle	Old
Rwanda	**83.4 %**	**17.8 %**	**2.8 %**	**45.1 %**	**35.1 %**	**20.1 %**
R1	77.9 % (**−5.5pp**)	16.3 % (**−1.5pp**)	3.6 % (**+0.8pp**)	+3.5pp	−1.5pp	−2.1pp
R2	88.2 % (**+4.8pp**)	13.1 % (**−4.7pp**)	0.3 % (**−2.5pp**)	+7.2pp	−2.8pp	−4.4pp
R3	80 % (**−3.4pp**)	20.9 % (**+3.1pp**)	5.6 % (**+2.8pp**)	−6.8pp	+3.5pp	+3.5pp
R4	93.9 % (**+10. pp**)	18.3 % (**+0.5pp**)	0.8 % (**−2pp**)	+12.8pp	−7.3pp	−5.7pp
R5	91.1 % (**+7.7pp**)	29.9 % (**+12.1pp**)	0.7 % (**−2.2pp**)	−4.3pp	+2.1pp	+2.4pp
R6	87.2 % (**+3.8pp**)	17.8 % (**0pp**)	1.2 % (**−1.6pp**)	−2.4pp	+0.3pp	+2.1pp
Kenya	**80.2 %**	**18.5 %**	**6.8 %**	**59.8 %**	**27.5 %**	**12.7 %**
K1	76.5 % (**−3.7pp**)	20.2 % (**+1.7pp**)	6 % (**−0.8pp**)	+0.4pp	−2.7pp	+2.3pp
K2	87.2 % (**+7pp**)	11.4 % (**−7.1pp**)	0.2 % (**−6.6pp**)	+9.8pp	−4.4pp	−5.5pp
K3	78.1 % (**−2.1pp**)	20.7 % (**+2.3pp**)	11.3 % (**+4.5pp**)	−5.6pp	+4.2pp	+1.4pp
K4	89.5 % (**+9.3pp**)	37.6 % (**+19.1pp**)	1.2 % (**−5.7pp**)	−7.3pp	+0.1pp	+7.3pp

Notes: For each cluster, both the absolute share and relative difference of users in each category is shown. The relative difference is highlighted in boldface and presented in percentage points (pp), and is calculated in relation to the overall share of users in a given category for the respective country.
[a] The maturity brackets correspond to the following intervals: Young [0, 2] years, Middle [2, 3] years, Old >3 years.

assumption – i.e., K2 and R2 – are also those who benefit more from the current PAYGo design. Indeed, even between the two, K2 – with the shortest *Pay* – seems to benefit the most. That is, these segments make ample use of the short-term flexibility the model concedes (i.e., via high *PLP* values) to nevertheless achieve high payment performances; just as the PAYGo design principals intended.

On the opposite end of the spectrum, monthly payers seem to benefit the least from the PAYGo model. Crucially, the current design expects users to amend a missed payment within short and flexible cycles; however, some of the segments identified show signs of being constrained to monthly cycles. In clusters K4, R4, and R5 this is evidenced by their strict 30 day *Pay* values and small pay variability, but also by their *CDU* values. Returning to Figs. 1 and 2, one finds that the *M-CDU* distribution of these clusters is strongly dominated by local maxima corresponding to 30, 60, and 90 days in the original scale; thus showing a monthly cycle restriction in their inability to pay.

Interestingly, a similar *CDU* analysis would suggest that Rwanda's cluster R6 may also be capturing monthly payers; which is in line with their similar performance profiles in Table 8. However, unlike the latter, their very high payment variability would imply that these are monthly users who can nevertheless react in more flexible payment cycles. This increased adaptability could also help explain R6's lower default rate when compared to R5s - i.e., the monthly cluster with a similar maturity profile.

A Preferred Payment Cycle (PPC) frame of reference helps to explain how the current PAYGo design may inadvertently be overburdening low payment frequency user segments. Firstly, in the event of a missed payment, high frequency payers will only experience a few days of lockout, as PPCs are naturally short. Whereas monthly payers face either a full month of lockout or must potentially resort to extraordinary means (e.g., savings or loans) to shorten their PPC. Secondly, default thresholds are also experienced much differently by the two groups. Before breaching the 120 days without credit threshold, K2 and R2 users will have on average missed 45 and 27 PPCs, respectively; while monthly payers default on the 4th missed PPC; resulting in significantly different experiences of leniency. Thirdly, current penalties and incentives fail to motivate compliance in long PPC users. For instance, the 7-day minimum payment penalty has no effect on monthly users, since, unlike other segments, their late payment size[4] is virtually the same as their *Pay* (i.e., 30 days).

If changing ones PPC implies a considerable effort for the average user, then exposing users with long PPCs to the factors above could explain their higher default rates with otherwise high payment performances. Although strict monthly segments only represent a small fraction, these frictions may be discouraging people from obtaining SHSs, while it is ostracising existing good users. In addition, if cluster R6 represents monthly payers who are often forced to change their PPCs, this would suggest a much greater share of SHS users is facing unintended financial pressure because of the current PAYGo design.

Conclusion

This study addresses the gap in our understanding of PAYGo SHS user payment patterns by examining the behavioural diversity exhibited in a sample containing over 32,000 Rwandan and 25,000 Kenyan customers. Three clustering algorithms were used to identify the main behavioural clusters in each country separately. The results highlight six behavioural clusters in Rwanda and four in Kenya. Most customer segments prefer following a weekly or monthly payment regime, rather than daily or high frequency payments. However, clusters with the highest natural payment cycles (i.e., closest to daily regimes) had the best payment performance despite a high share of missed payments; just as the model design expects. Conversely, rigid monthly payers, are the worst performers. While strict monthly payers may represent a small share of users, a closer analysis reveals that there may be a higher share of more adaptable monthly payers. Regardless, payment patterns are likely to reflect tangible constraints (e.g., income streams), thus implying that deviations from these patterns are likely to cause additional financial stresses – e.g., in the use of savings or loans.

More research is needed in order to verify to what extent the different behavioural groups are discontent with the current PAYGo model design. Nevertheless, this study already demonstrates that not addressing the needs of users with different behavioural profiles results in inefficiencies. Therefore, it is recommended that PAYGo providers consider more tailored plans, adjusted to the variety of users they intend to serve. The challenge lies in reimagining what a similar amount of leniency and flexibility currently offered to short PPC users could look like for longer PPC customers.

These efforts could greatly benefit from a continued focus on data-driven research, which would help to further contextualize and inform new designs. For instance, identifying which sociodemographic factors contribute to the emergence of these payment groups would help to understand why they emerge and how to cater for them. Additionally, assessing how behaviours change over time may reveal more nuanced patterns (e.g., seasonal cycles) and help preventively detect and support users at risk of default. Ultimately, given the scarcity of literature, there is great potential to improve how the PAYGo model is implemented and thus scale up the reach of SHSs and energy access.

[4] Late payment size is calculated the same way as *Pay*, however, it only accounts for payments done when late – i.e., with zero time-credit in balance.

CRediT authorship contribution statement

Vasco P. Mergulhão: Conceptualization, Data curation, Methodology, Investigation, Formal analysis, Validation, Visualization, Writing – original draft. **Licia Capra:** Supervision, Methodology, Writing – review & editing. **Kostas Voglitsis:** Data curation, Resources. **Priti Parikh:** Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kostas Voglitsis reports a relationship with Bboxx Ltd. that includes: employment. Vasco Mergulhao reports a relationship with Bboxx Ltd. that includes: funding grants and travel reimbursement. Priti Parikh reports a relationship with Bboxx Ltd. that includes: funding grants.

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Glossary

PAYGo: Pay-as-you-go
SHS: Solar Home System
SSA: Sub-Saharan Africa
SDG7: Sustainable Development Goal 7
MFIs: Microfinance Institutions
HC: Hierarchical Clustering
CVI: Clustering Validation Index
DB: Davies-Bouldin index
Sil: Silhouette index
CVNN: Clustering Validation index based on Nearest Neighbours
KPIs: Key Performance Indicators
CR: Collection rate
PPC: Preferred Payment Cycle.