POLICY BRIEF

FINCA®

Research and Data Science

MEASURING WOMEN'S ECONOMIC EMPOWERMENT:

IMPLICATIONS FOR PROGRAM DESIGN AND EVALUATION

KEY RESULTS

- Standardized measures of empowerment do not capture the reality of women's complex financial lives. Under rigorous statistical scrutiny, most of the best-known women's economic empowerment (WEE) metrics — such as private control over financial information or income — had *no correlation* with actual savings behavior among female customers of FINCA Uganda.

- The statistically meaningful indicators — such as household financial responsibilities, future outlook, exposure to financial literacy training, and financial strategies for old age — were highly localized and developed inductively over the course of our study. The one standard WEE construct that showed validity was decision-making power, though it had both positive and negative associations.

- While standardized metrics can offer a useful point of reference, practitioners and evaluators should take care to develop WEE measures in the context of their specific interventions, in order to avoid the high risk of measurement error. For indicators to be relevant and meaningful, they should be grounded in the lived experience of the women being targeted.

- Financial coaching produced varied results depending on the profile of the women who participated. Those with higher indices of vulnerability were better able to set *meaningful goals,* while women who were comparatively more empowered were better able to make *actual savings* deposits.

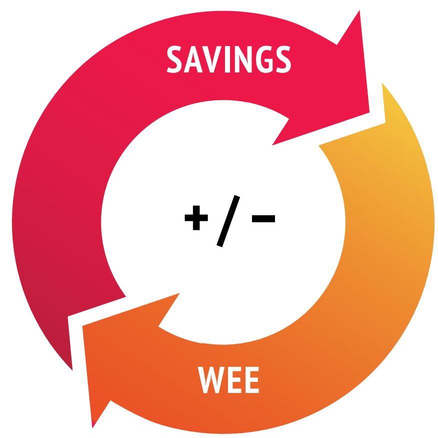
Rigorous statistical validation shows that WEE indicators must be derived locally, not applied directly from standardized frameworks. In the context of any specific intervention, the empowerment indicators that have the strongest empirical relationship with actual financial behavior may differ from what is widely considered "standard."

DEVELOPING STATISTICALLY VALID INDICATORS

The need for concrete WEE metrics is not disputed, but the first challenge is figuring out *what to measure.* Standardized frameworks offer some guidance, but they must be carefully adapted to the context of a specific intervention — and even then, they are likely to miss important local factors. Our study focused on a savings account for women in Uganda, with digital features such as remote onboarding, goal setting, and a network of banking agents. We devised an extensive battery of WEE indicators and collected survey data from 1,498 account users, along with their savings histories from the bank's management information system. We then used machine learning feature-selection algorithms to identify the WEE variables that could successfully predict *actual* savings behavior. Our observed outcomes included the ability to set meaningful goals, make savings deposits toward those goals, and use the savings purposefully.

DIVING INTO COMPLEXITY

Our research started with a series of focus group discussions and cognitive interviews to uncover the motivations, barriers, and enablers of women's formal savings. It quickly became clear that financial and social empowerment are deeply intertwined in women's day-to-day savings journeys. Specific financial responsibilities, such as school expenses, can strongly motivate a woman to save in her account. But the causal relationship also works *in the opposite direction,* where a woman's savings defines her financial role in the family. The two issues are entangled, with no consistent directionality between them. Women also described empowerment and savings as having *both positive and negative connotations,* depending on the circumstances. For example, having private control over their financial information facilitates independent control over women's resources, but it can also cause discord and mistrust in the family, with negative repercussions. We took great care to ensure that our validation model encompassed both the entanglement and bidirectional aspects of women's lived experiences.



DATA AND ANALYSIS

Based on the results of the qualitative phase, we developed a wide-ranging battery of WEE indicators, which we administered through surveys at baseline and endline. To encompass the complexity described above, we used the survey responses to construct a dataset of 238 independent WEE features, which we combined with account-level transactions. The data was randomly divided between training and validation sets, following a standard machine-learning workflow.

As explained in detail **here**, we used a variety of feature-selection algorithms — Least Squares Selection (LSS), Variable Selection Using Random Forests (VSURF), and Boruta — on the training data to identify an optimal combination of WEE/savings indicators that had the strongest correlation with actual savings behavior. Our two best-performing feature sets, derived via LSS, contained seven and 32 indicators, respectively. Applied to the validation data, our selected features produced a higher correlation than 99% of the randomly constructed (out-of-bag, or OOB) simulations, numbering in the thousands.

VALIDATION RESULTS

Perhaps the most striking result is just how *few* of our WEE/savings indicators showed any statistical relationship with actual savings behavior. Although over 230 empowerment indicators were tested, a set of just seven variables performed as well as much larger models with 30 or more variables. Beyond these, additional variables merely introduced noise and reduced the model's accuracy. The fact that a small, context-specific subset of indicators captured nearly all of the predictive signal highlights both the *potential* and the *risk* of measuring empowerment: When indicators are not carefully derived and validated within the context of a specific outcome and intervention, measurement becomes noisy or diluted. This suggests that women's savings decisions are shaped by multiple factors, of which WEE is one important but not exclusive dimension.

The below table summarizes our validation results by showing how frequently each WEE indicator was selected by any of our feature-selection algorithms.

When reading this table, it is important to remember that our approach does not assign any specific *value* to the indicator: Each metric contains *both* positive and negative influences. For example, the most frequently selected indicator, household financial responsibilities, captures instances where such responsibilities had the effect of *increasing* savings but also ones where they *undermined* it. Instead of these instances canceling each other out, our model adds them together, showing the *total influence* of this factor. This value-neutral approach strongly reveals the importance of family dynamics (in the frequency of family disagreements and support for women's savings efforts) as well as personal traits such as future outlook and overall life satisfaction. One of the most frequently selected indicators, financial strategies for old age, was unique to our study, while metrics that are more prevalent in the WEE field — such as being forced to disclose income, confidence in expressing opinions, and time-control limitations — were rarely selected.

WEE INDICATORS

HIGHEST

Household financial responsibilities (school fees, etc.)	88%
Future outlook	75%
Exposure to financial literacy training (savings, budgeting, etc.)	75%
Financial strategies for old age	67%
Ability to compare various financial products	63%
Decision-making power	63%
Overall life satisfaction	54%
Family disagreements	54%
Family support for women's saving efforts	50%

LOWEST

Forced to disclose income against will	38%
Confidence in expressing opinions	33%
Perception of the importance of private savings	25%
Budgeting practices and timeframes	25%
Time-control limitations (who and what)	17%
Existence of savings role models	4%
Preference for digital channels vs. physical location	4%

THE EFFECT OF FINANCIAL COACHING

Half of the women in our study (750) were randomly assigned to receive personalized financial coaching. Through a further round of validation, we found that our previously selected indicators actually performed *better* among the coaching clients than among the control group. We conclude that financial coaching strengthened the empirical relationship between WEE and savings. Since our model does not presume directionality, the practical interpretation of this finding is that financial coaching strengthens the influence of empowerment on savings, while also strengthening the influence of savings on empowerment.

Intrigued by this finding, we used additional machine-learning techniques (classification analysis and generic machine learning with sorted group average treatment effects) to discern *which WEE/savings* features had the strongest association with specific savings outcomes. This analysis showed that the effects of coaching varied according to the type of women receiving it. Women who were more socially vulnerable (fewer long-term assets, less family support, and lower confidence) gained the ability to set meaningful goals — i.e., goals that persisted from baseline to endline. For women who were comparatively less vulnerable (already more knowledgeable about savings, had attended some kind of training, enjoyed greater financial privacy, and had a more optimistic outlook), coaching resulted in a stronger record of savings deposits toward their goals.

FINAL REFLECTIONS

Digital financial services have the **potential to empower women**, but they do not operate in a vacuum. If we want to generate positive outcomes for women, we need to rigorously observe the dynamics at play. As an empirical task, this requires metrics that are not only adapted to the local context but that reliably show some robust connection between empowerment and financial services. Otherwise, we may be overlooking the most important factors — such as the strong influence of financial responsibilities or concerns about aging — while focusing on other factors — like confidence and control over one's time — that ultimately have little bearing on the outcomes.

Measurement is more straightforward where WEE metrics relate to *access* and *usage*, which can be directly observed through administrative data. But when our goal is to generate measurable change in *financial empowerment,* there is no way to avoid the complexity of the issue. Our empirical approach has to account for local social dynamics and personal experiences that are deeply embedded in the very notion of *empowerment*. Qualitative research can describe these issues very well (up to the point of *saturation* or completeness), but it leaves us blind to their relative influence on observed behavior.

A targeted measurement study can clarify the specific pathways through which empowerment intersects with savings decisions. But measurement studies are rare, and most WEE interventions and evaluations will necessarily proceed without one. Our findings show a delicate empirical relationship between empowerment and savings, which should warn practitioners and researchers alike against the high risk of measurement error. Starting with a concrete, localized framework mitigates this risk and allows for the formulation of empowerment metrics that are fit for purpose, interpretable, and aligned with program objectives.

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