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Beyond Access: Operationalizing Digital Inclusion through a Usage-Based Personal Digital Inclusion Index

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ABSTRACT

Digital inclusion discourse has progressively shifted from binary measures of access to nuanced considerations of meaningful use. However, a critical gap persists: the absence of a standardized, individual-level metric that captures the depth of digital engagement beyond mere connectivity. Addressing the first research objective of a larger study, this paper empirically demonstrates that service usage complexity is a valid indicator of digital inclusion and develops a Personal Digital Inclusion Index (DII). Drawing on Sen's Capability Approach and survey data from 292 digitally vulnerable users in rural Kenya, we rank six digital service types by complexity and frequency of use. Chi-square ($\chi^2(5)=142.834$, $p<.001$) and ANOVA ($F(5,1746)=89.26$, $p<.001$) analyses confirm a significant, progressive decline in usage as service complexity increases. Leveraging the weighted sum model (WSM) with rank-sum-derived weights, we construct a composite DII that quantifies an individual's position from basic access to deep, functional inclusion. The resulting index offers policymakers, researchers, and practitioners a robust, replicable tool to measure digital capabilities, identify functional exclusion, and design targeted interventions that move beyond infrastructural metrics to foster genuine digital participation.

Keywords- Digital Inclusion Index, ICT4D, Capability Approach, Service Usage, Weighted Sum Model, Digital Divide, Kenya

I. INTRODUCTION

The transformative potential of digital technologies in fostering socio-economic development is now beyond dispute [1], [2]. Governments and private entities globally have accelerated the provision of electronic services (e-services), recognizing their cost-effectiveness and capacity to enhance citizen convenience [3], [4]. Kenya exemplifies this trajectory, with innovations like M-Pesa, eCitizen, and mobile banking fundamentally reshaping financial and public service landscapes [5].

However, a persistent challenge has emerged: the functional digital divide or "usage gap." While physical access to mobile phones and network connectivity has expanded dramatically, a significant portion of the population remains confined to basic transactions—such as sending or receiving money—and does not progress to more complex, higher-value digital engagements like online purchases, remote banking, or digital credit [6]. This disparity reveals a critical flaw in traditional digital inclusion metrics, which have largely prioritized supply-side indicators: device ownership, network coverage, and subscription rates [7].

This narrow focus overlooks the quality and depth of digital participation. As argued by Sen's Capability Approach [8], well-being is not merely about the resources one possesses (e.g., a phone) but about the capabilities and functionings one can achieve (e.g., securely obtaining a loan online). Thus, a person with a mobile phone who can only perform basic transfers is less digitally included than one who uses the same device to manage investments, pay bills, and access e-government services. Current metrics fail to capture this crucial distinction.

This paper addresses this gap by responding to the first objective of a broader doctoral study: *To establish infrastructure access and service-based factors that affect digital usage levels among users*. Specifically, we argue that before modeling the drivers of digital inclusion, one must first establish a valid measure of the outcome—digital usage depth. Consequently, this paper pursues two aims:

To empirically demonstrate that digital service usage levels, ordered by complexity, serve as a valid and significant indicator of digital inclusion.

To develop, justify, and present a robust Personal Digital Inclusion Index (DII) that operationalizes this usage-based conceptualization, providing a replicable tool for researchers and practitioners.

The paper proceeds as follows: Section 2 reviews relevant literature on the evolution of digital inclusion metrics and the Capability Approach. Section 3 outlines the methodology, including the survey instrument and analytical techniques (Chi-square, ANOVA, Weighted Sum Model). Section 4 presents the empirical results showing the significant decline in usage across complexity levels. Section 5 details the construction and justification of the DII. Section 6 discusses the implications for research, policy, and practice.

II. LITERATURE REVIEW

A. The Evolution of Digital Inclusion Metrics

Early digital divide research focused dichotomously on "haves" versus "have-nots" regarding physical access to computers and the internet [9]. Consequently, inclusion metrics were simplistic: number of internet subscriptions, mobile phone penetration, or broadband availability [10]. While laying essential infrastructure groundwork, this approach proved inadequate. As Mervyn [11] notes, access without the ability to use meaningfully does not confer inclusion.

A significant critique has emerged from the ICT4D community. Sharp [7] explicitly states that metrics for the quality of use remain "relatively underdeveloped." Similarly, Sabri et al. [12] acknowledge the lack of metrics to measure different dimensions of digital inclusion, particularly the use dimension. Most indices aggregate national-level data, obscuring individual heterogeneity and failing to identify who is excluded from which benefits. Dezuanni et al. [13] call for metrics that measure the "digital ability" dimension—the capacity to convert access into valued outcomes.

B. The Capability Approach as a Theoretical Lens

To address this lacuna, we adopt Sen's Capability Approach (CA) [8]. The CA distinguishes between resources (means), capabilities (freedoms to achieve), and functionings (achieved beings and doings). Applied to digital inclusion, a mobile phone is a resource. The capability is the freedom to use it for diverse purposes—communication, finance, learning. The functioning is the actual act of, for example, applying for a digital loan [14]. Digital inclusion, therefore, should be measured by the range and complexity of functionings a person can effectively achieve [15]. A person who owns a phone but only makes calls (a low-level functioning) has lower digital capability than one who uses the same resource for banking, e-commerce, and e-government (high-level functionings). Our study operationalizes this by ranking digital functionings by complexity.

C. The Missing Link: Technology Adoption Models and the Usage Gap

While the Capability Approach provides the why (inclusion as freedom to achieve functionings), it does not fully explain the how—the psychological and behavioral mechanisms that determine whether an individual converts access into actual use. This is where technology adoption models become essential. As extensively reviewed in the foundational literature, a significant body of research has sought to understand why users accept or reject information systems. These models bridge the gap between resource possession (a mobile phone) and achieved functioning (using it for a loan).

The Technology Acceptance Model (TAM) [16] posits that two primary beliefs drive technology adoption: perceived usefulness (the degree to which a person believes a technology will enhance their performance) and perceived ease of use (the degree to which a person believes using the technology will be free of effort). TAM suggests that for a digitally vulnerable user, even if they have access to a smartphone (a resource), they will not progress to complex functionings (e.g., online banking) unless they perceive the system as useful and easy to navigate.

The Unified Theory of Acceptance and Use of Technology (UTAUT) [17] offers a more comprehensive lens. It synthesizes eight competing models, including TAM, the Theory of Reasoned Action, and the Theory of Planned Behavior. UTAUT identifies four core constructs:

Performance Expectancy (similar to perceived usefulness);

Effort Expectancy (similar to perceived ease of use);

Social Influence (the degree to which an individual perceives that important others believe they should use the system); and

Facilitating Conditions (the belief that an organizational and technical infrastructure exists to support use).

Critically, UTAUT also includes moderators (age, gender, experience, voluntariness of use), acknowledging that adoption pathways are heterogeneous. This is highly relevant for digital inclusion, where vulnerable groups (the elderly, low-literacy users) may face distinct barriers not captured by a one-size-fits-all model.

Other models, such as the Diffusion of Innovation (DOI) theory [18], contribute the insight that adoption is not instantaneous but a process. Rogers identified that an innovation's relative advantage, compatibility, complexity, trialability, and observability influence its adoption rate. For digital services, high complexity (a construct directly related to usability and security friction) is a powerful predictor of slower adoption and higher exclusion.

Despite their strengths, these adoption models have a critical limitation when applied to digital inclusion: they typically conceptualize "usage" as a binary or continuous variable (e.g., intention to use, frequency of use), but they do not differentiate the quality or depth of that usage. A user who frequently sends money (a low-level functioning) and a user who frequently applies for digital loans (a high-level functioning) would both register as "high adopters" in TAM/UTAUT, obscuring a significant inclusion disparity. As noted in the parent study, "most adoption models barely go beyond the mere usage level... they have not sought to evaluate how much inclusion results from motivating the user to adopt the technology."

D. Towards an Integrated Framework: From Adoption to Inclusion Depth

The argument advanced in this paper is that a synthesis is required. Technology adoption models (TAM, UTAUT, DOI) provide the predictive machinery—the constructs that explain why one user progresses while another stagnates. These include perceived ease of use (directly related to security usability), effort expectancy, social influence, facilitating conditions, and perceived risk (trust). The Capability Approach [8] provides the normative outcome—the measure of what constitutes meaningful inclusion: the achievement of diverse and complex digital functionings.

This integrated perspective directly informs the present study's first objective. Before we can model how factors like security usability or cost affect inclusion (the subject of subsequent objectives), we must first develop a valid metric for the outcome: digital usage depth. The current literature lacks such a metric [7], [12]. Existing adoption studies typically use simplistic dependent variables (e.g., "do you use mobile money? yes/no"), which conflate basic access with deep, transformative use.

Consequently, this paper responds to a clear, two-part gap identified in the literature:

Conceptual Gap: While adoption models explain if a technology is used, they do not measure how deeply it is used. The Capability Approach supplies the normative framework for depth, but lacks an operationalized metric.

Methodological Gap: There is no standardized, individual-level index that quantifies digital inclusion as a function of achieved service complexity.

Therefore, the remainder of this paper addresses these gaps by (a) empirically validating that usage complexity is a meaningful stratifier of digital inclusion (Section 4), and (b) developing a replicable Personal Digital Inclusion Index (DII) that operationalizes this concept, thereby providing the necessary dependent variable for subsequent modeling of adoption drivers (Section 5).

III. METHODOLOGY

A. *Research Design and Sampling*

This study is part of a larger cross-sectional survey grounded in critical realism. Data were collected in rural Central Kenya, targeting populations vulnerable to digital marginalization based on literacy, age, and income. Using purposive and random sampling, 292 valid responses were obtained from lower-grade employees in learning institutions, agricultural estates, and open-air market vendors. The sample comprised 50.7% male and 49.3% female, with 62.3% having secondary education or lower, ensuring representation of digitally vulnerable users.

B. *Instrument and Variables*

A structured questionnaire captured six digital usage levels (Table 1), ordered a priori by the researcher based on process complexity, authentication requirements, and perceived risk. This order was subsequently validated empirically. Respondents indicated their frequency of use for each level on a 5-point Likert scale (1="Strongly Agree/Always" to 5="Strongly Disagree/Not at all").

TABLE 1. DIGITAL USAGE LEVELS BY COMPLEXITY

Level	Description	Complexity
1	Having a bank account or using a phone to access digital service	Basic Access
2	Sending/receiving money (mobile) or ATM withdrawal	Basic Transaction
3	Paying for goods/services in local stores using mobile/ATM	Medium Transaction
4	Paying for goods/services online	Advanced Transaction
5	Remote operation of bank accounts (mobile to bank transfers)	Advanced Management
6	Obtaining loans via mobile money or mobile banking	High-Risk / Complex

C. *Analytical Strategy*

We employed two inferential tests to validate usage levels as an inclusion indicator:

Chi-Square Test to determine if the proportion of users varies significantly across the six levels.

One-Way ANOVA to test for significant differences in mean usage frequency across levels.

Based on these validations, we constructed a Personal Digital Inclusion Index (DII) using the Weighted Sum Model (WSM) with rank-sum-derived weights, a standard method in multi-criteria decision analysis when criteria can be ordinally ranked [19].

IV. RESULTS: USAGE LEVELS AS INDICATORS OF DIGITAL INCLUSION

A. *Descriptive Trends*

Table 2 summarizes the percentage of respondents who agreed/strongly agreed to using services at each level.

TABLE 2. USAGE FREQUENCY ACROSS COMPLEXITY LEVELS (N=292)

Level	Description	Agree/Strongly Agree (%)
1	Access (Account/Phone)	94.5
2	Basic Transaction (Send/Withdraw)	78.8
3	Local Payment	63.0
4	Online Payment	47.9
5	Remote Banking	45.2
6	Digital Loans	19.2

A clear, monotonic decline is evident. While near-universal agreement exists for Level 1 (access), adoption drops precipitously for advanced services, with only one-fifth of respondents using digital loan facilities.

B. *Inferential Validation*

The Chi-Square test revealed a statistically significant difference in usage frequencies across the six levels ($\chi^2(5) = 142.834$, $p < .001$). The One-Way ANOVA confirmed a significant difference in mean usage scores ($F(5, 1746) = 89.26$, $p < .001$). Tukey HSD post-hoc comparisons (Table 3) further validated the ordinal nature of the scale.

TABLE 3. SELECTED TUKEY HSD POST-HOC COMPARISONS

Comparison	Mean Difference	p-value	Significance
Level 1 vs. Level 6	-2.26	<.001	Significant
Level 2 vs. Level 6	-1.61	<.001	Significant
Level 4 vs. Level 5	0.00	.999	Not Significant

(Lower mean = more frequent use on 1-5 scale)

All comparisons between distinct complexity levels (1 vs. 6, 2 vs. 6, 1 vs. 4) were significant at $p < .001$. Notably, Levels 4 (online payment) and 5 (remote banking) showed no significant difference ($p = .999$), suggesting a plateau in moderate usage before the final drop to Level 6 (loans). These results empirically confirm that usage frequency is inversely proportional to service complexity, validating the use of complexity-ranked usage levels as a robust indicator of digital inclusion depth.

V. DEVELOPING THE PERSONAL DIGITAL INCLUSION INDEX (DII)

A. *Rationale for a Composite Index*

Given the proven stratification of usage, a single, composite score is needed to quantify an individual's overall digital inclusion. A simple sum of usage frequencies would ignore the greater importance (weight) of higher-level functionings. Borrowing from microeconomic theory, a preference order satisfying monotonicity (more complex use is better), translation invariance (relative disparities matter), and substitutability (higher-level use can compensate for lower-level non-use) can be represented by a weighted sum [20]. The usage levels meet these axioms.

B. *Weight Determination using Rank-Sum Method*

We assigned ranks (r) from 1 (least inclusive) to 6 (most inclusive) to the six usage levels. Using the rank-sum weight formula [21]:

$$\omega_r = \frac{(N - r + 1)}{\sum_{k=1}^{N}(N - k + 1)} = \frac{(6 - r + 1)}{21}$$

TABLE 4. RANK-SUM WEIGHTS FOR DIGITAL USAGE LEVELS

Rank (r)	Usage Level	Weight (w_r)
1 (Lowest)	Level 1 (Access)	6/21 ≈ 0.286
2	Level 2 (Basic Transaction)	5/21 ≈ 0.238
3	Level 3 (Local Payment)	4/21 ≈ 0.190
4	Level 4 (Online Payment)	3/21 ≈ 0.143
5	Level 5 (Remote Banking)	2/21 ≈ 0.095
6 (Highest)	Level 6 (Digital Loans)	1/21 ≈ 0.048

Higher-level functionings receive lower weights because they represent deeper inclusion; a low raw score (high frequency) on a highly weighted level contributes less to the index than a low raw score on a low-weighted level, appropriately valuing advanced capabilities.

C. The Digital Inclusion Index (DII) Formula

Applying the Weighted Sum Model, the Personal Digital Inclusion Index for an individual i is calculated as:

$$DII_i = \sum_{j=1}^{6}(w_j \times X_{ij})$$

Where w_j is the weight from Table 4, and X_{ij} is the raw Likert score (1-5) for usage level j for individual i (where 1 indicates highest use). Thus, lower DII scores indicate deeper digital inclusion. The equation can the be written as;

Equation:

DIIi=(UL1×6/21) +(UL2×5/21) +(UL3×4/21) +(UL4×3/21) +(UL5×2/21) +(UL6×1/21)

VI. DISCUSSION

A. Contribution: A Valid, Usage-Centric Metric

This paper makes a foundational contribution by moving digital inclusion measurement from access to achieved functioning. The statistically significant stratification of usage levels (Section 4) provides empirical justification for ranking digital activities by complexity. The resulting DII is not merely a theoretical exercise; it is an operational tool grounded in user behavior. Unlike national-level indices (e.g., ITU's IDI), the DII is individual-level, enabling nuanced analysis of intra-population disparities. It addresses Sharp's [7] critique by explicitly incorporating the "quality of use" dimension of inclusio.

B. Application for Research and Policy

For researchers, the DII serves as a robust dependent variable. It allows for precise modeling of the drivers of inclusion—such as security usability, trust, and cost—as intended in the broader study. For policymakers, the DII offers a diagnostic tool. Instead of merely counting connections, a government could survey a representative sample, compute DII scores, and identify: (a) what proportion of the population is stuck at Level 1-2 (functional exclusion), and (b) which specific advanced services (e.g., loans, online payments) present the greatest barrier. Interventions can then be targeted precisely: digital literacy campaigns for online payments, usability audits for loan application interfaces, or trust-building for e-commerce. For practitioners (e.g., banks, mobile network operators), the DII can segment users to design tailored onboarding and upskilling pathways.

C. Limitations and Future Work

The DII's current form is context-specific to rural Kenya and the services surveyed. The weights are derived from this sample's frequency order; in a different context (e.g., urban, high-literacy), the rank order might differ. Future research should validate the DII across diverse populations and potentially derive weights through more sophisticated methods (e.g., Analytical Hierarchy Process). Furthermore, the DII assumes a linear additive model; interaction effects between usage levels are not captured. Despite these limitations, the index provides a crucial first step toward standardized, capability-oriented measurement of digital inclusion.

VII. CONCLUSION

This paper addressed the critical gap in measuring how digitally included individuals truly are, beyond binary access metrics. Using empirical data from digitally vulnerable users in Kenya, we demonstrated that digital service usage declines significantly and progressively with increasing complexity. Based on this validation, we developed a robust, replicable Personal Digital Inclusion Index (DII) grounded in Sen's Capability Approach and operationalized through a weighted sum model. The DII offers a significant advancement for ICT4D research and practice, providing a nuanced, individual-level metric that captures the depth of digital functioning. By enabling the measurement of real inclusion, this index empowers stakeholders to design and evaluate interventions that foster not just connectivity, but genuine, equitable participation in the digital economy.

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