

# Making green finance actionable: overall enablement and domain configuration in household green-technology adoption

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## Article

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# Abstract

Green finance can reduce the upfront burden of household low-carbon technologies, yet perceived access does not necessarily translate into adoption. We develop a financial actionability perspective that distinguishes a common level of household enablement from the configuration of ten financial, cognitive-relational, feasibility, operational, and contextual domains. Using cross-sectional survey data from 2,529 adult household decision-makers in Vietnam, we compare nested predictive representations using training-only model selection and held-out evaluation. Demographics alone performed worse than a mean-only benchmark (test  $R^2 = -0.128$ ). Test  $R^2$  increased to 0.394 with green-finance availability, 0.675 with the overall enablement index, and 0.754 with the differentiated ten-domain specification. Domain configuration added  $\Delta R^2 = 0.079$  beyond overall enablement (95% bootstrap CI [0.045, 0.117]), whereas selected nonlinear and product probes added no reliable predictive value. The first principal component accounted for 80.8% of domain-score variance, indicating a strong common enablement core, and leave-one-domain-out analysis showed the largest performance loss when household financial stability was removed. The results support a two-layer account in which green finance is an entry condition rather than a stand-alone solution: financial opportunity is more actionable when households can understand, trust, manage, and implement it within a broader enabling architecture. The evidence is predictive, cross-sectional, self-reported, and non-causal.

## 1. Introduction

Household adoption of energy-efficient and low-carbon technologies is both a consumer decision and a component of wider sustainability transitions. Green credit, concessional finance, instalment products, and related instruments can ease capital constraints, and research at firm and regional levels links green finance to investment, innovation, and environmental outcomes (Chen and Chen, 2025; Dai et al., 2025; Sun et al., 2025). At household level, however, financing does not automatically translate into action. Adoption still depends on whether households can evaluate technologies, manage costs and timing, trust providers, and navigate implementation. Recent studies likewise show that household energy decisions vary with awareness, trust, perceived benefits and sacrifice, education, information, and financial constraints, and that adopters and non-adopters may follow different decision paths (Paramita et al., 2024; Shi et al., 2026; Silvikko et al., 2025).

This creates a practical and theoretical gap. A financing offer can be formally available yet remain difficult to understand or trust, poorly aligned with household cash flow, digitally inaccessible, or operationally burdensome. Households also face uncertainty about technology performance, installers, after-sales service, policy continuity, and the timing of savings. The relevant question is therefore not only whether finance exists, but whether it can be converted into credible, manageable, and usable action. We use financial actionability to describe this conversion capacity: the extent to which a financing opportunity can be translated into feasible household adoption rather than remaining nominally available.

Existing research identifies many elements of this conversion process, but usually in separate literatures. Household-finance research emphasises liquidity, information, trust, planning horizons, and financial capability (Campbell, 2006; Gomes et al., 2021; Guiso et al., 2008; van Rooij et al., 2011). Research on sustainable financial consumption links financial literacy, product quality, and accessible technologies to responsible financial behaviour (Dash and Mohanta, 2025). Research on energy finance and digital financial inclusion points to the joint relevance of financing and digital access for sustainability outcomes (Xia and Fatema, 2025). Behavioural-energy studies show that salience, subsidy design, payment timing, and time discounting shape technology uptake (Allcott and Taubinsky, 2015; De Groote and Verboven, 2019). Technology-adoption research highlights usefulness, usability, social support, and facilitating conditions (Brown and Venkatesh, 2005; Davis, 1989; Venkatesh et al., 2003, 2012).

Sustainability-transition research further emphasises policy mixes, infrastructure, business models, after-sales support, peer effects, and household agency (Agrawal et al., 2022; Bollinger and Gillingham, 2012; Bollinger et al., 2024; Raven et al., 2021, 2025; Rogge and Reichardt, 2016). Micro-level evidence also shows that access to information can shape green-technology decisions through awareness, preferences, and risk perceptions (Zhang et al., 2025). The unresolved problem is how to organise these strongly interrelated conditions theoretically. A finance-centred account is too narrow when formal access is unusable in practice, whereas an additive model of fully independent drivers can overstate empirical distinctiveness when enabling conditions move together.

The enabling-architecture perspective addresses this problem through two analytically distinct layers. Overall enablement captures the shared strength of conditions that make household action possible. Domain configuration captures the relative pattern across green-finance availability, legibility, credibility, temporal fit, digital financial inclusion, technological capability, policy support, social network support, socioeconomic resources, and household financial stability. The distinction is substantive rather than merely statistical: households with similar overall support can still face different bottlenecks, and those differences may carry predictive information about current adoption engagement.

The empirical design tests this argument through nested information sets: demographics alone; demographics plus green-finance availability; demographics plus an overall enablement index; demographics plus the differentiated ten-domain vector; and the domain specification plus selected nonlinear and product probes. This sequence asks whether finance adds information beyond demographics, whether broader enablement adds information beyond finance, whether configuration adds information beyond common level, and whether selected nonlinear or pairwise terms add anything further. The study contributes by reframing green finance in terms of actionability, distinguishing architecture-level coherence from domain-level configuration, and using out-of-sample prediction to compare increasingly differentiated theoretical representations. The contribution is predictive and theory-organising; it does not establish causal effects, formal complementarity, verified environmental savings, or population prevalence.

## 2. Theoretical Background and Analytical Framework

## 2.1. From green-finance access to financial actionability

Many residential green technologies require substantial upfront expenditure while delivering benefits over a longer horizon. Financing can ease liquidity constraints, smooth payments, and make an otherwise infeasible investment possible. This logic is consistent with household-finance research showing that major decisions depend on liquid resources, financial sophistication, trust, advice, and decision context (Campbell, 2006; Gomes et al., 2021; Guiso et al., 2008; von Gaudecker, 2015). It also aligns with evidence that subsidy design, payment timing, and discounting affect adoption even when long-run benefits are positive (Allcott and Taubinsky, 2015; De Groote and Verboven, 2019), and with broader evidence that green-finance effects often operate through financing conditions and investment or innovation channels (Chen and Chen, 2025; Dai et al., 2025).

Access nevertheless remains only an entry condition. A household may perceive that credit or instalment products exist but hesitate because terms are unclear, repayment feels risky, digital application channels are difficult to navigate, providers are not trusted, policy support appears unstable, or installation and maintenance capabilities are weak. Reviews of household energy transitions identify intertwined information, financial, technological, social, housing, and policy barriers (Chadwick et al., 2022; Du et al., 2022; Hesselink and Chappin, 2019). Residential technology studies similarly show that adoption depends on motivations and constraints that vary across technologies and household circumstances (Antonopoulos et al., 2024; Chen and Shi, 2026; Girod et al., 2017; Mateus et al., 2023; Outcault et al., 2022). Information access can also alter awareness, decision preferences, and perceived risk surrounding green technologies (Zhang et al., 2025).

Financial actionability is therefore defined here as the extent to which a household can understand, trust, manage, and use a green-finance opportunity in ways that make reported current adoption practically feasible. It is related to financial literacy and technology facilitating conditions but is not reducible to either: financial literacy concerns knowledge and capability, whereas facilitating conditions concern support for technology use; financial actionability concerns whether a specific financing opportunity can be converted into feasible adoption through a wider configuration of financial, informational, relational, operational, and contextual supports (van Rooij et al., 2011; Venkatesh et al., 2003, 2012). It is therefore a system-level conversion concept rather than a single household trait or belief. The concept does not imply that the present study verifies installations, measures realised energy savings, or observes emission reductions.

## 2.2. Enabling architecture: level and configuration

An architecture is more than a list of independent determinants. It is an organised set of conditions whose collective strength and relative arrangement shape whether an opportunity can be acted upon. The logic is informed by complementarities, in which the usefulness of one element can depend on others (Milgrom and Roberts, 1990), but the present study does not claim to establish supermodularity, necessity, or causal interaction. Complementarity is used as system-level theoretical motivation; the

empirical test concerns the incremental predictive information contained in overall level and differentiated configuration.

The first layer, overall enablement level, captures the common strength shared across the domains. A household that reports clear offers, credible providers, manageable timing, capable digital use, strong policy support, and stable resources is broadly enabled; weak conditions may likewise accumulate. This common level is theoretically meaningful because green-technology adoption requires a sequence of tasks: understanding, financing, applying, installing, operating, and maintaining. Together, these tasks draw on a shared household capacity to act.

The second layer, domain configuration, captures how enablement is distributed. Two households can have the same overall average but different bottlenecks: one may have financing and digital access but weak credibility; another may trust providers but lack financial stability or repayment fit. A differentiated domain specification should therefore add information beyond a single overall score when relative patterns matter. This level-configuration distinction also provides a principled response to high correlations among enabling conditions: shared variance represents the architecture level, whereas incremental predictive value from the domain vector represents configuration.

## **2.3. Components of the enabling architecture**

The empirical architecture comprises ten theory-informed indicators. Green-finance availability (GFA) captures perceived access to financing that reduces upfront burden or spreads payment over time. Legibility (LEG) concerns the clarity of terms, eligibility, benefits, risks, and implementation steps. Credibility (CRE) captures trust in lenders, installers, intermediaries, utilities, and public commitments. LEG and CRE are cognitive-relational conditions that reduce ambiguity and vulnerability (Campbell, 2006; Guiso et al., 2008; Mayer et al., 1995; Schoorman et al., 2007).

Temporal fit (TF) and household financial stability (HFS) are feasibility conditions. A financing arrangement may appear affordable in total but remain impractical when payment timing conflicts with income flows or when households lack buffers against temporary shocks. Household-finance and solar-adoption research shows that liquidity, repayment timing, and discounting shape major investment decisions (Campbell, 2006; De Groote and Verboven, 2019; Gomes et al., 2021). Energy-justice research further emphasises unequal household capacities to absorb transition costs and risks (Holt and Sunter, 2024; Konzen et al., 2024).

Digital financial inclusion (DFI) and technological capability (TECH) are operational conditions. Digital channels increasingly mediate information search, applications, documentation, payments, and after-sales communication, but nominal access does not ensure confident use. Technology-adoption research consistently shows that usability, capability, and facilitating conditions affect whether systems generate value (Brown and Venkatesh, 2005; Davis, 1989; Venkatesh et al., 2003, 2012). Recent evidence also links digital financial inclusion to sustainable-development pathways and shows that information access can

broaden green-technology adoption (Dumo, 2026; Xia and Fatema, 2025; Zhang et al., 2025). Digital participation in household energy transitions remains socially differentiated (Thunshirn et al., 2025).

Policy support (PS), social network support (SNS), and socioeconomic resources (SES) are contextual conditions. Policy support can reduce uncertainty by signalling incentive continuity and institutional backing (Peng et al., 2026); macro-level evidence likewise indicates that policy uncertainty and green-finance effectiveness are intertwined (Hoang et al., 2026; Sun et al., 2025). Social networks transmit information, visibility, reassurance, and observational learning (Aral and Walker, 2011; Bollinger and Gillingham, 2012; Bollinger et al., 2024; Gillingham and Bollinger, 2021). Households also rely on practical peer information when evaluating complex renewable-energy options (Silvikko et al., 2025). Socioeconomic resources affect the capacity to absorb risk, mobilise complementary inputs, and manage implementation demands, leaving adoption opportunities unevenly distributed (Holt and Sunter, 2024; Konzen et al., 2024; Mahieu et al., 2025).

## 2.4. Analytical expectations

The enabling-architecture perspective yields four expectations. First, demographic characteristics should provide limited predictive leverage because they are distal proxies rather than direct measures of whether a household can understand, finance, and implement an adoption decision; adding GFA should improve prediction because finance is an important entry condition. Second, an overall enablement index should add substantial predictive information beyond the finance-only specification if actionability depends on a broader architecture-level capacity rather than financial availability alone.

Third, the differentiated ten-domain vector should improve prediction beyond the overall enablement index if relative domain configuration matters even when the domains share substantial variance. This is the key empirical distinction between a purely common-level account and the proposed two-layer architecture.

Fourth, a limited set of centred nonlinear and product probes may add little once the domain vector is included. The architecture is theorised primarily at system and configuration levels; isolated pairwise products are not expected to exhaust its structure and are not treated as formal moderation tests. Figure 1 summarises the theoretical framework and its mapping onto the five empirical comparisons.

The analytical expectations therefore separate common enablement from differentiated configuration without assuming that every domain is an independent latent construct or that any selected pairwise interaction represents causal complementarity.

## 3. Methods

### 3.1. Research design

The study uses a cross-sectional household survey to examine reported green-technology adoption engagement as a form of responsible household consumption. The analysis is designed for theory-

informed predictive comparison rather than causal estimation. The primary task is continuous prediction of reported current adoption engagement. Secondary analyses examine a broader four-item engagement index, the original five-item index, and future expansion intention. These measures represent self-reported engagement rather than verified installations, realised energy savings, or emission reductions. This positioning follows calls to combine explanatory theory with transparent out-of-sample prediction while recognising that complex human outcomes remain only partially predictable (Hofman et al., 2021; Lundberg et al., 2024).

The empirical strategy combines nested feature-block comparisons, training-only model selection, held-out evaluation, paired bootstrap uncertainty for incremental  $R^2$ , and leave-one-domain-out ablation. The design asks whether predictive information resides primarily in finance, common enablement, or differentiated configuration rather than treating algorithmic complexity as theoretical evidence.

## **3.2. Data collection and analytical sample**

Primary data were collected through a structured household survey administered in Vietnam from late May through June 2026. Participation was voluntary, and informed consent was obtained before respondents proceeded. Eligible participants were adult residents who were primary or joint decision-makers for major household purchases and had basic awareness of residential clean-energy technologies or green-finance options. Recruitment used online distribution, community networks, and referrals. The de-identified analytical file does not retain province-level identifiers or respondent-level recruitment-channel indicators; geographic and channel-specific coverage therefore cannot be reconstructed from the analysis-ready data. The resulting non-probability sample is not claimed to represent the Vietnamese household population.

The questionnaire covered household background, green-finance availability, product and process clarity, trust in intermediaries, repayment compatibility, digital and technological capability, policy and social support, household resources, and reported adoption. The source dataset contained 2,568 records. Two exact duplicate rows were removed. Because exact birthdays were unavailable, a conservative adult-eligibility rule excluded 37 respondents reporting birth years after 2007. The final analytical sample contained 2,529 complete observations. Only variables specified for the present analysis were retained in the analysis-ready file.

Same-source, same-wave measurement creates residual common-method risk, including the possibility that shared response tendencies or generalised positive evaluations contribute to observed associations. Procedural safeguards included clear wording, thematic separation, structured organisation, and screening for duplicate and eligibility problems, consistent with established guidance (Podsakoff et al., 2003, 2024). These procedures reduce but cannot eliminate common-method variance. Held-out prediction evaluates generalisation within the present measurement system; it does not remove same-source bias or convert self-reports into verified behaviour. Results are therefore interpreted as predictive associations requiring validation against temporally separated or externally verified outcomes.

## **3.3. Measures and architecture diagnostics**

Each architecture domain was represented by the arithmetic mean of five seven-point agreement items. The instrument was developed from the enabling-architecture framework and administered in Vietnamese. The Vietnamese version was prepared through forward translation, reconciliation, and independent back-translation. Domain-specific Cronbach's alpha values ranged from 0.937 to 0.971, indicating high internal consistency; because coefficients of this magnitude can also reflect item redundancy, they are not treated as evidence of construct validity or empirical distinctiveness.

The ten scores are not treated as fully discriminant reflective latent constructs. Instead, they are theory-informed composite indicators of an interdependent architecture. An overall enablement index (EA) was calculated as the unweighted mean of the ten domain scores, which share the same response scale. Principal-component analysis of standardised domain scores was used as a structural diagnostic of common architecture-level variance. The differentiated domain vector was then compared with EA out of sample; this comparison tests whether configuration adds information beyond common level.

The primary outcome, reported current adoption engagement (ADOPT-C), is the arithmetic mean of ADOPT1-ADOPT3. These items capture current use of energy-efficient appliances, adoption of at least one clean-energy or low-carbon household technology, and active investment in household energy efficiency. The index therefore represents a broad engagement continuum rather than a homogeneous or externally verified adoption event. ADOPT4, comparative progress relative to similar households, is added in the four-item robustness index ADOPT-4. The original five-item ADOPT index additionally includes ADOPT5, future expansion intention. ADOPT5 is also analysed separately as ADOPT-I. This hierarchy prevents future intention and comparative self-assessment from defining the primary behavioural outcome.

### 3.4. Nested predictor sets

Five predictor sets were specified. X1 contains gender, age, education, marital status, occupation, job position, employment length, and household income. X1G adds GFA. X1E adds the overall enablement index EA rather than the individual domains. X2 includes demographics and all ten domain scores. X3 adds six supplementary probes to X2: squared centred GFA and the products  $GFA \times PS$ ,  $DFI \times TECH$ ,  $CRE \times SNS$ ,  $TF \times HFS$ , and  $GFA \times SES$ . These derived features were constructed by mean-centring the corresponding domain scores before squaring or multiplication. X3 is used only to examine whether selected nonlinearities or pairwise combinations add predictive information beyond X2; it is not interpreted as a moderation or formal complementarity test. The central architecture comparison is X1E versus X2.

### 3.5. Model comparison and evaluation

The data were divided into 80% training and 20% held-out test samples. To preserve the continuous outcome distribution, the split was stratified by ADOPT-C quintiles using seed 20260529. Model-fitting preprocessing was estimated within the training data: categorical demographics were one-hot encoded, and scaling was applied where required by the estimator. Model selection and all outcome-based tuning were confined to the training sample; held-out outcomes were used only for final performance

evaluation, reducing outcome leakage and optimistic performance estimates (Kapoor and Narayanan, 2023).

Four regression benchmarks were compared under X2: ridge regression, Random Forest, Extremely Randomised Trees (Extra Trees), and histogram gradient boosting. Extra Trees randomises candidate split thresholds and provides a flexible ensemble benchmark for nonlinear structure (Geurts et al., 2006). Primary model selection was based only on mean RMSE from five-fold shuffled cross-validation within the training sample. A supplementary five-repeat, five-fold comparison of the two leading tree ensembles assessed selection stability without using the test set. The held-out test set was then used once for final MAE, RMSE, and  $R^2$  evaluation. Percentile intervals for selected-model test metrics were obtained from 1,500 bootstrap resamples of held-out cases.

After model selection, the same estimator specification was used across X1-X3 so that performance differences reflected predictor information rather than changes in algorithm. Paired bootstrap resampling of held-out cases produced 95% intervals for  $R^2$  differences between adjacent feature sets. An incremental difference was treated as reliable when its interval excluded zero. The split seed, model-comparison procedure, resampling design, and evaluation metrics are reported to support analytical transparency and replication.

## **3.6. Domain ablation and robustness**

Leave-one-domain-out ablation was conducted for X2 by refitting the selected estimator after removing each domain. The change in held-out  $R^2$  identifies whether a domain contributes information that cannot readily be reconstructed from the remaining correlated domains. Because correlated predictors can redistribute attribution, the analysis prioritises ablation and nested block comparisons over single-feature importance rankings.

Robustness checks re-estimated the selected X2 model for ADOPT-4, the original five-item ADOPT index, and ADOPT-I. Descriptive enablement strata based on EA tertiles were calculated only to illustrate the outcome gradient and were not interpreted as latent household types or targeting rules.

## **3.7. Reproducibility**

The reproducibility protocol records source-data cleaning, score construction, probe construction, the stratified split, model specifications, cross-validation seeds, held-out evaluation, bootstrap comparisons, ablation, and figure generation. The de-identified analysis-ready data and variable codebook are supplied as supplementary peer-review materials and document the retained variables, composite-score derivations, outcome definitions, and derived probe variables. The split seed and evaluation procedure are reported in the manuscript to support analytical transparency and reconstruction.

# **4. Results**

## **4.1. Analytical sample and descriptive statistics**

The final analytical sample contained 2,529 respondents. Mean age was 37.8 years (SD = 12.7). Women represented 60.0% of the sample, bachelor-degree holders were the largest education group, and 61.4% were married. Table 1 describes the retained sample. Because recruitment was non-probability based, these distributions characterise the analytical sample rather than national prevalence.

Table 1  
Respondent characteristics

| Characteristic                                                                                                                                       | Category/statistic         | n     | % or SD |
|------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|-------|---------|
| Gender                                                                                                                                               | Woman                      | 1,518 | 60.0    |
| Gender                                                                                                                                               | Man                        | 995   | 39.3    |
| Gender                                                                                                                                               | Other/prefer not to say    | 16    | 0.6     |
| Age                                                                                                                                                  | Mean (SD)                  | 37.8  | 12.7    |
| Age                                                                                                                                                  | 18–29 years                | 768   | 30.4    |
| Age                                                                                                                                                  | 30–39 years                | 532   | 21.0    |
| Age                                                                                                                                                  | 40–49 years                | 833   | 32.9    |
| Age                                                                                                                                                  | 50–59 years                | 277   | 11.0    |
| Age                                                                                                                                                  | 60 years or older          | 119   | 4.7     |
| Education                                                                                                                                            | Upper secondary or below   | 368   | 14.6    |
| Education                                                                                                                                            | College/diploma            | 232   | 9.2     |
| Education                                                                                                                                            | Bachelor degree            | 1,464 | 57.9    |
| Education                                                                                                                                            | Postgraduate degree        | 403   | 15.9    |
| Education                                                                                                                                            | Other                      | 62    | 2.5     |
| Marital status                                                                                                                                       | Single                     | 834   | 33.0    |
| Marital status                                                                                                                                       | Married                    | 1,553 | 61.4    |
| Marital status                                                                                                                                       | Divorced/widowed           | 140   | 5.5     |
| Marital status                                                                                                                                       | Other                      | 2     | 0.1     |
| Monthly household income                                                                                                                             | Lowest reported category   | 649   | 25.7    |
| Monthly household income                                                                                                                             | Middle reported categories | 1,671 | 66.1    |
| Monthly household income                                                                                                                             | Highest reported category  | 209   | 8.3     |
| <i>Note: Percentages may not sum to 100 because of rounding. Income labels preserve the ordered categories available in the analytical codebook.</i> |                            |       |         |

Table 2 summarizes the source-record screening, analytical split, and outcome definitions used in the subsequent models.

Table 2  
Analytical sample, split, and outcome definitions

| Indicator                                                                                                                                                                | Value                            |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------|
| Records in source file                                                                                                                                                   | 2,568                            |
| Exact duplicate rows removed                                                                                                                                             | 2                                |
| Conservative adult-eligibility exclusions                                                                                                                                | 37                               |
| Final analytical sample                                                                                                                                                  | 2,529                            |
| Training sample                                                                                                                                                          | 2,023                            |
| Held-out test sample                                                                                                                                                     | 506                              |
| Mean ADOPT-C, training                                                                                                                                                   | 4.797                            |
| Mean ADOPT-C, test                                                                                                                                                       | 4.798                            |
| Primary outcome                                                                                                                                                          | ADOPT-C = mean of ADOPT1-ADOPT3  |
| Robustness outcomes                                                                                                                                                      | ADOPT-4; original ADOPT; ADOPT-I |
| <i>Note: The split was stratified by ADOPT-C quintiles. Exact birthdays were unavailable; respondents reporting birth years after 2007 were excluded conservatively.</i> |                                  |

Mean ADOPT-C was 4.797 (SD = 1.440). Among the architecture domains, GFA had the highest mean (5.316), whereas HFS had the lowest (4.601). Table 3 reports domain means and standard deviations.

Table 3  
Descriptive statistics of the enabling-architecture domains

| Domain                                                                                                              | Mean  | SD    |
|---------------------------------------------------------------------------------------------------------------------|-------|-------|
| GFA                                                                                                                 | 5.316 | 1.090 |
| LEG                                                                                                                 | 5.090 | 1.195 |
| CRE                                                                                                                 | 4.984 | 1.271 |
| TF                                                                                                                  | 5.228 | 1.050 |
| DFI                                                                                                                 | 5.236 | 1.067 |
| TECH                                                                                                                | 5.021 | 1.225 |
| PS                                                                                                                  | 5.018 | 1.240 |
| SNS                                                                                                                 | 5.221 | 1.071 |
| SES                                                                                                                 | 5.005 | 1.195 |
| HFS                                                                                                                 | 4.601 | 1.497 |
| <i>Note: All domain scores range from 1 to 7. Higher HFS values indicate greater household financial stability.</i> |       |       |

## 4.2. Architecture-level coherence

The domain indicators displayed strong common structure. The first principal component accounted for 80.8% of standardised domain-score variance, whereas the second component accounted for 6.5%. First-component loadings were positive and relatively even across the ten domains (0.276–0.325). Cronbach's alpha calculated across the ten domain scores was 0.971. These diagnostics indicate substantial architecture-level commonality and reinforce the decision not to present the domain scores as independent reflective latent constructs. The key empirical question is therefore whether retaining differentiated domain information improves out-of-sample prediction beyond the common level.

## 4.3. Benchmark model performance

Table 4 compares the four X2 regression benchmarks. Extra Trees had the lowest primary training cross-validated RMSE (0.776), narrowly ahead of Random Forest (0.778), and was therefore selected before test-set evaluation. A supplementary five-repeat, five-fold analysis confirmed that the two ensembles were effectively tied: mean RMSE was 0.773 (SD = 0.044) for Extra Trees and 0.775 (SD = 0.044) for Random Forest, with Extra Trees performing better in 13 of 25 matched folds. The model-class difference is not interpreted substantively; the training-only selection rule prevents retrospective choice based on test performance.

Table 4  
Benchmark regression performance for the differentiated domain specification (X2)

| Model                                                                                                                                                                 | CV MAE | CV RMSE | CV R <sup>2</sup> | Test MAE | Test RMSE | Test R <sup>2</sup> |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|---------|-------------------|----------|-----------|---------------------|
| Ridge                                                                                                                                                                 | 0.519  | 0.814   | 0.680             | 0.528    | 0.770     | 0.712               |
| Random Forest                                                                                                                                                         | 0.466  | 0.778   | 0.707             | 0.467    | 0.730     | 0.741               |
| Extra Trees                                                                                                                                                           | 0.476  | 0.776   | 0.709             | 0.467    | 0.712     | 0.754               |
| Histogram Gradient Boosting                                                                                                                                           | 0.504  | 0.807   | 0.685             | 0.489    | 0.745     | 0.731               |
| <i>Note: CV values are means across five shuffled training folds. Model selection used training CV RMSE only. X2 includes demographics and the ten domain scores.</i> |        |         |                   |          |           |                     |

On the held-out test set, the selected Extra Trees model achieved MAE = 0.467, RMSE = 0.712, and R<sup>2</sup> = 0.754. The bootstrap 95% interval for test R<sup>2</sup> was [0.709, 0.794]. Figure 2 shows the predicted-versus-observed pattern for the 506 held-out cases.

## 4.4. Incremental value of finance, overall enablement, and domain configuration

The nested comparison provides the central test of the enabling-architecture argument. Demographics alone performed worse than a mean-only benchmark (test R<sup>2</sup> = -0.128). Adding GFA increased test R<sup>2</sup> to 0.394. Replacing the single finance indicator with the overall enablement index raised test R<sup>2</sup> to 0.675. The differentiated ten-domain specification further increased test R<sup>2</sup> to 0.754. Adding the centred nonlinear and product probes did not improve held-out performance and reduced test R<sup>2</sup> slightly to 0.751 (Table 5).

Table 5  
Incremental predictive value of nested feature sets

| Feature set                                                                                                                                                                           | Predictor block                           | CV RMSE | CV R <sup>2</sup> | Test RMSE | Test R <sup>2</sup> |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|---------|-------------------|-----------|---------------------|
| X1                                                                                                                                                                                    | Demographics only                         | 1.574   | -0.196            | 1.525     | -0.128              |
| X1G                                                                                                                                                                                   | X1 + green-finance availability           | 1.210   | 0.293             | 1.117     | 0.394               |
| X1E                                                                                                                                                                                   | X1 + overall enablement index             | 0.926   | 0.585             | 0.819     | 0.675               |
| X2                                                                                                                                                                                    | X1 + ten differentiated domains           | 0.776   | 0.709             | 0.712     | 0.754               |
| X3                                                                                                                                                                                    | X2 + centred nonlinear and product probes | 0.771   | 0.713             | 0.717     | 0.751               |
| <i>Note: The same Extra Trees specification was used for every feature set. EA is the unweighted mean of the ten domain scores. Probe terms were constructed after mean centring.</i> |                                           |         |                   |           |                     |

Paired bootstrap comparisons support the three substantive gains. GFA improved  $R^2$  over demographics by 0.522 (95% CI [0.430, 0.624]); overall enablement improved  $R^2$  over the finance-only model by 0.280 (95% CI [0.222, 0.347]); and differentiated domain information improved  $R^2$  over overall enablement by 0.079 (95% CI [0.045, 0.117]). The X3 increment was  $-0.004$  and its interval included zero (95% CI [-0.013, 0.005]). Figure 3 summarises held-out performance across the five feature sets.

## 4.5. Domain ablation

The X2-X1E difference shows that the domain vector matters collectively, but strong correlations make isolated importance rankings fragile. Leave-one-domain-out ablation therefore asks whether any domain supplies information that cannot readily be reconstructed from the remaining nine. Removing HFS produced the largest performance loss, reducing test  $R^2$  by 0.042 from 0.754 to 0.712. Removing SES or SNS produced much smaller losses, while several removals produced negligible improvements consistent with redundancy and sampling variation (Table 6).

Table 6  
Leave-one-domain-out ablation for the selected X2 model

| Domain removed | Test $R^2$ | $\Delta R^2$ versus X2 | Interpretation           |
|----------------|------------|------------------------|--------------------------|
| HFS            | 0.712      | -0.042                 | Largest performance loss |
| SES            | 0.750      | -0.004                 | Small performance loss   |
| SNS            | 0.752      | -0.002                 | Small performance loss   |
| DFI            | 0.753      | -0.002                 | Negligible change        |
| TECH           | 0.754      | -0.000                 | Negligible change        |
| CRE            | 0.754      | + 0.000                | Negligible change        |
| LEG            | 0.754      | + 0.000                | Negligible change        |
| TF             | 0.756      | + 0.002                | Negligible change        |
| PS             | 0.757      | + 0.003                | Negligible change        |
| GFA            | 0.758      | + 0.004                | Negligible change        |

*Note: Negative  $\Delta R^2$  indicates lower performance after removing a domain. Small positive changes reflect redundancy or sampling variation and do not imply that a domain is causally harmful.*

Figure 4 visualises the held-out  $R^2$  loss associated with removing each domain from the selected X2 model.

## 4.6. Outcome-definition robustness

The central pattern was robust to alternative outcome definitions. Using ADOPT-4, which adds comparative adoption progress to the three primary items, produced test  $R^2 = 0.764$ . The original five-item index produced test  $R^2 = 0.774$ . Future expansion intention alone was less predictable but remained substantial (test  $R^2 = 0.676$ ). These checks indicate that the architecture is associated with both current engagement and future intention while preserving current engagement as the conceptually cleaner primary outcome (Table 7).

Table 7  
Outcome-definition robustness for the selected X2 model

| Outcome        | Definition                         | Test MAE | Test RMSE | Test $R^2$ |
|----------------|------------------------------------|----------|-----------|------------|
| ADOPT-C        | Mean of ADOPT1-ADOPT3              | 0.467    | 0.712     | 0.754      |
| ADOPT-4        | Mean of ADOPT1-ADOPT4              | 0.446    | 0.696     | 0.764      |
| Original ADOPT | Mean of ADOPT1-ADOPT5              | 0.436    | 0.670     | 0.774      |
| ADOPT-I        | ADOPT5: future expansion intention | 0.545    | 0.813     | 0.676      |

## 5. Discussion

### 5.1. Main findings

This study examined why perceived access to green finance translates unevenly into reported current household green-technology adoption. Four findings define the answer. First, demographic characteristics carried little out-of-sample predictive information, whereas green-finance availability substantially improved prediction. Second, overall enablement performed considerably better than green-finance availability alone, indicating that financial access is embedded in a broader household capacity to act. Third, the differentiated ten-domain specification improved prediction beyond overall enablement, showing that relative configuration carries meaningful information even when the domains share a strong common core. Fourth, the centred nonlinear and product probes added no reliable predictive value once differentiated domain information was included.

The improvement from finance-only to overall enablement is consistent with research showing that household energy adoption reflects interconnected financial, informational, technological, social, and institutional conditions rather than a single barrier (Chadwick et al., 2022; Hesselink and Chappin, 2019; Raven et al., 2021). It also complements evidence that awareness, trust, peer information, education, and immediate financial constraints shape household energy choices (Paramita et al., 2024; Shi et al., 2026; Silvikko et al., 2025; Zhang et al., 2025). The present study adds a distinct organising claim: common enablement and differentiated configuration are not competing representations but two levels of the same household action architecture.

The combination of principal-component and nested-prediction evidence is important for interpretation. A first component explaining 80.8% of variance indicates substantial commonality and would be

inconsistent with treating the ten domains as fully independent latent constructs. Under the enabling-architecture perspective, this shared variance represents common enablement rather than a reason to discard differentiated information. The more demanding test is whether the domain vector adds predictive information beyond that common level. The increase from X1E to X2 indicates that it does. Households with similar overall enablement may therefore differ in reported adoption engagement because the relative distribution of financial, cognitive-relational, feasibility, operational, and contextual conditions differs.

## **5.2. Green finance as an entry condition for responsible consumption**

The finance-only comparison provides direct evidence that perceived green-finance availability is meaningful but incomplete. Moving from demographics to GFA produced a large increase in held-out predictive performance, consistent with evidence that subsidies, financing arrangements, and payment timing affect technology adoption (Agrawal et al., 2022; Allcott and Taubinsky, 2015; De Groote and Verboven, 2019). At broader scales, green finance has also been linked to sustainable investment through financing and innovation channels (Chen and Chen, 2025; Dai et al., 2025). The household-level question addressed here is what converts such financial opportunity into action.

Overall enablement added 0.280 in held-out  $R^2$  beyond the finance-only model, and differentiated configuration added a further 0.079 beyond overall enablement. These increments indicate that the practical value of finance is associated with whether households can understand the offer, trust the actors involved, align repayment with cash flow, navigate digital processes, evaluate and operate the technology, and rely on sufficiently supportive institutional and social conditions.

This interpretation refines rather than rejects finance-centred explanations. Financing may be especially important for capital-intensive household technologies, but formal availability does not guarantee practical usability. Previous studies similarly show that adoption depends on financial conditions alongside technology characteristics, trust, information, policy arrangements, and implementation capability (Antonopoulos et al., 2024; Mateus et al., 2023; Outcault et al., 2022; Paramita et al., 2024; Pham and Le, 2026). Financial actionability locates finance within the broader conversion process through which a cleaner-consumption opportunity becomes feasible household action.

## **5.3. Overall enablement and domain configuration**

The distinction between overall level and domain configuration contributes to multi-domain adoption theory. Models that force strongly correlated supports into separate and fully independent constructs risk overstating discriminant structure. Yet models that collapse all enabling conditions into a single index may overlook meaningful relative bottlenecks. The present evidence supports a middle position: the domains form a coherent architecture with a strong common level, but retaining their differentiated scores improves out-of-sample prediction.

This position is consistent with household-transition research identifying mutually reinforcing financial, informational, technological, social, and institutional barriers (Chadwick et al., 2022; Du et al., 2022; Raven et al., 2021). The enabling-architecture perspective adds precision by separating the common strength of those conditions from their relative distribution. Two households may have the same overall enablement score but differ in the source of constraint: one may have finance and digital capability but weak provider credibility; another may understand and trust the technology but lack financial stability or repayment fit.

The level-configuration distinction is also methodologically disciplined. The overall index provides a parsimonious benchmark and makes common variance explicit. The differentiated model must then justify its additional complexity through improved prediction, which it does in the held-out sample. By contrast, the selected nonlinear and pairwise probes do not improve performance. Their null incremental value cautions against using a small number of interaction terms to claim statistical or theoretical complementarity in a highly interconnected system.

## **5.4. Household financial stability as a distinctive constraint**

Household financial stability produced the largest leave-one-domain-out loss by a substantial margin. Removing HFS reduced test  $R^2$  from 0.754 to 0.712, whereas removing the other domains produced much smaller changes. This pattern suggests that income predictability, repayment capacity, and financial buffers contain predictive information that is not readily reconstructed from perceived finance availability, socioeconomic resources, temporal fit, or the remaining domains.

The result is consistent with household-finance research showing that major investment decisions depend not only on formal access to finance but also on liquidity, income stability, repayment capacity, and precautionary buffers (Campbell, 2006; Gomes et al., 2021). A household may perceive a loan as available and still be unwilling or unable to accept repayment risk when income is volatile, emergency reserves are limited, or unexpected expenses could disrupt planned payments. The finding also aligns with energy-justice research documenting unequal capacities to absorb the costs and risks of residential energy transitions (Holt and Sunter, 2024; Konzen et al., 2024).

The comparatively small ablation losses for the remaining domains should not be read as evidence that credibility, legibility, digital capability, policy support, or social support are unimportant. The domains are strongly correlated, so predictive information can be redistributed among closely related scores. Removing one domain can leave several substitutes in the model. The defensible conclusion is therefore about uniqueness, not absolute importance: HFS appears less redundant within this particular architecture, whereas the unique contributions of several other domains are difficult to isolate in a same-wave, highly correlated measurement system.

## **5.5. Theoretical contributions**

First, the study advances financial actionability as a household-level conversion concept. Unlike financial literacy, which concerns knowledge and capability, or facilitating conditions, which concern support for

technology use, financial actionability describes whether a specific financing opportunity can be translated into feasible adoption through a wider configuration of financial, relational, operational, and contextual supports. This shifts attention from nominal access or household capability in isolation to the conversion process linking financial opportunity with action.

Second, the study develops a two-layer enabling architecture. Overall enablement represents the common strength of conditions that support household action, whereas domain configuration represents the relative pattern of strengths and constraints within that common level. The formulation avoids two problematic extremes: assuming that all domains are fully independent or assuming that they are completely interchangeable. The evidence is consistent with a coherent common core that still contains differentiated predictive information.

Third, the study demonstrates how predictive validation can be used to discipline theory comparison. The sequence from demographics to finance, overall enablement, differentiated domains, and nonlinear and pairwise probes maps directly onto alternative theoretical representations. Training-only model selection, held-out outcome evaluation, paired bootstrap comparisons, repeated cross-validation, and leave-one-domain-out ablation distinguish block-level conclusions from unstable single-feature attribution.

The methodological contribution therefore does not rest on the novelty of a particular machine-learning algorithm. It lies in using out-of-sample performance as a demanding test of whether increasingly differentiated theoretical representations carry information beyond simpler alternatives, while keeping causal and measurement claims appropriately bounded.

## **5.6. Policy and practical implications**

The findings suggest that expanding the supply of green finance alone may leave substantial responsible-consumption gaps. Financing programmes should be evaluated together with the conditions that make offers understandable, credible, manageable, and usable. Depending on technology and population, candidate components include simplified disclosures, transparent eligibility rules, verified installer networks, stable incentive information, assisted digital applications, and repayment schedules aligned with household cash-flow patterns. Broader evidence also points to the importance of digital financial inclusion and policy conditions in connecting finance to sustainability outcomes (Sun et al., 2025; Xia and Fatema, 2025). These implications are design propositions for subsequent testing, not causal effects established by the present observational study.

Household financial stability deserves particular attention. For households with volatile income or limited buffers, flexible repayment, temporary payment relief, contingency provisions, income-sensitive underwriting, or protection against implementation failure may warrant experimental or pilot evaluation alongside conventional interest-rate reductions. Such designs could reduce repayment risk or perceived vulnerability, but their effectiveness, costs, and distributional consequences require direct evaluation.

The overall-enablement result also cautions against targeting households solely through broad demographic categories. Age, education, occupation, and income categories provided little predictive value when used alone, whereas more proximal enabling conditions were highly informative. Programme design should therefore diagnose actionable constraints directly rather than use demographics as substitutes for financial stability, understanding, trust, digital capability, or implementation readiness.

The configuration result further suggests that standardised interventions may be inefficient. Households with similar overall enablement may face different bottlenecks and therefore require different forms of support. The present evidence does not identify the causal effect of any intervention, but it offers a structured basis for designing and experimentally comparing differentiated policy and service packages.

## **5.7. Limitations and future research**

The findings are bounded by a cross-sectional, self-reported, non-probability sample in Vietnam. They do not establish temporal ordering, causal effects, nationally representative prevalence, verified installations, realised energy savings, emission reductions, or province-specific patterns. Reverse pathways are also plausible: households that have already adopted green technologies may subsequently report greater technological capability, provider trust, or perceived access to finance. The design cannot determine the direction of influence. ADOPT-C combines efficient-appliance use, adoption of at least one clean-energy or low-carbon technology, and active efficiency investment; it should therefore be interpreted as a broad reported engagement index rather than a homogeneous adoption event. Same-wave measurement may further inflate associations through shared response tendencies or generalised evaluative positivity (Podsakoff et al., 2003, 2024).

The study-developed items show high within-domain internal consistency, but strong cross-domain correlations preclude treating the ten scores as fully discriminant reflective constructs. The predictive framework also does not establish formal complementarity: the selected nonlinear and product probes did not improve held-out performance, and the architecture claim rests on block-level predictive information and configuration rather than pairwise moderation. Extra Trees was selected through training cross-validation, but its advantage over Random Forest was very small; the substantive interpretation therefore does not depend on the presumed superiority of one algorithm.

Future research should validate the enabling architecture in independent samples, countries, and technology categories. Probability-based or carefully designed quota samples would improve population inference, while linkage to verified installation, application, approval, transaction, energy-use, or billing records would reduce reliance on self-report. Longitudinal studies should distinguish successive stages of responsible adoption, including awareness, consideration, financing application, approval, installation, use intensity, realised savings, and repeat investment. Item-specific analyses should test whether the architecture performs similarly for efficient appliances, capital-intensive technologies, and active household investment.

Experimental and quasi-experimental designs could test whether interventions targeting legibility, credibility, repayment fit, digital support, technological capability, or household financial buffers change adoption behaviour. Measurement research should also compare alternative structures, including a general enablement factor, higher-order models, and domain-specific residual components, using separate calibration and validation samples. Such work would clarify whether the level-configuration distinction generalises beyond the present predictive setting.

## 5.8. Conclusion

Green-finance availability matters, but it does not fully explain reported current household green-technology adoption. The evidence is consistent with an enabling architecture that has two layers: a common level of household enablement and a differentiated configuration of financial, cognitive-relational, feasibility, operational, and contextual conditions. The common level captures much of the predictive signal, yet configuration adds meaningful information beyond that level.

Household financial stability emerges as the least redundant individual domain, indicating that access to finance cannot fully substitute for stable income, repayment capacity, or financial buffers. At the same time, the absence of improvement from centred nonlinear and product probes cautions against reducing an interconnected architecture to a small set of pairwise interactions.

The study therefore offers a bounded, predictive, and non-causal account of why financial opportunity becomes more actionable for some households than for others. Green finance is best understood not as a complete solution, but as one component of a wider architecture that can support cleaner and more responsible household consumption. Because the outcome is broad and self-reported, the findings are most appropriately used to organise future policy, service, and field experiments rather than to claim verified environmental impact.

## Declarations

### Data availability

The de-identified analysis-ready data and variable codebook supporting the reported analyses are provided as supplementary peer-review materials. Additional study materials may be made available by the corresponding author on reasonable request, subject to participant consent and applicable institutional data-sharing requirements. Any public repository record created at publication will be reported in the final article.

### Author contributions

All authors contributed to the conception or design of the study, analysis or interpretation of the data, critical revision of the manuscript, and approval of the final version.

### Competing interests

The authors declare no competing interests.

## Ethics declaration

On 6 October 2026, after reviewing the study materials solely to determine the applicable institutional ethics-review requirement, the Department for Management of Science & Technology Development (DEMASTED), Ton Duc Thang University, determined that formal institutional ethics-committee review was not required under TDTU policy reference No. 3096/QĐ-TDTU (29 August 2025). This determination does not constitute retrospective ethics approval. The study was a voluntary, non-interventional questionnaire survey of adult household decision-makers in Vietnam and involved no clinical or biomedical procedures, biological specimens, or health/medical data. The authors confirm that all research procedures were performed in accordance with applicable TDTU requirements and the Belmont Report principles for human-participant research (respect for persons, beneficence, and justice). All participants were adults, participation was voluntary, and informed consent was obtained before the questionnaire. The analysis-ready dataset was de-identified, and no directly identifying participant information is reported. Vietnam Ministry of Health Circular No. 43/2024/TT-BYT concerns ethics committees in biomedical research and is cited only to clarify the national biomedical-research ethics framework, not as a stand-alone exemption for non-biomedical social-science research.[1]

[1] TDTU institutional determination under policy reference No. 3096/QĐ-TDTU (29 August 2025), supplied with the revision. Ministry of Health of Vietnam, Circular No. 43/2024/TT-BYT, Article 1, Official National Database of Legal Documents: <https://vbpl.vn/TW/Pages/vbpq-print.aspx?ItemID=172919>

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## Figures

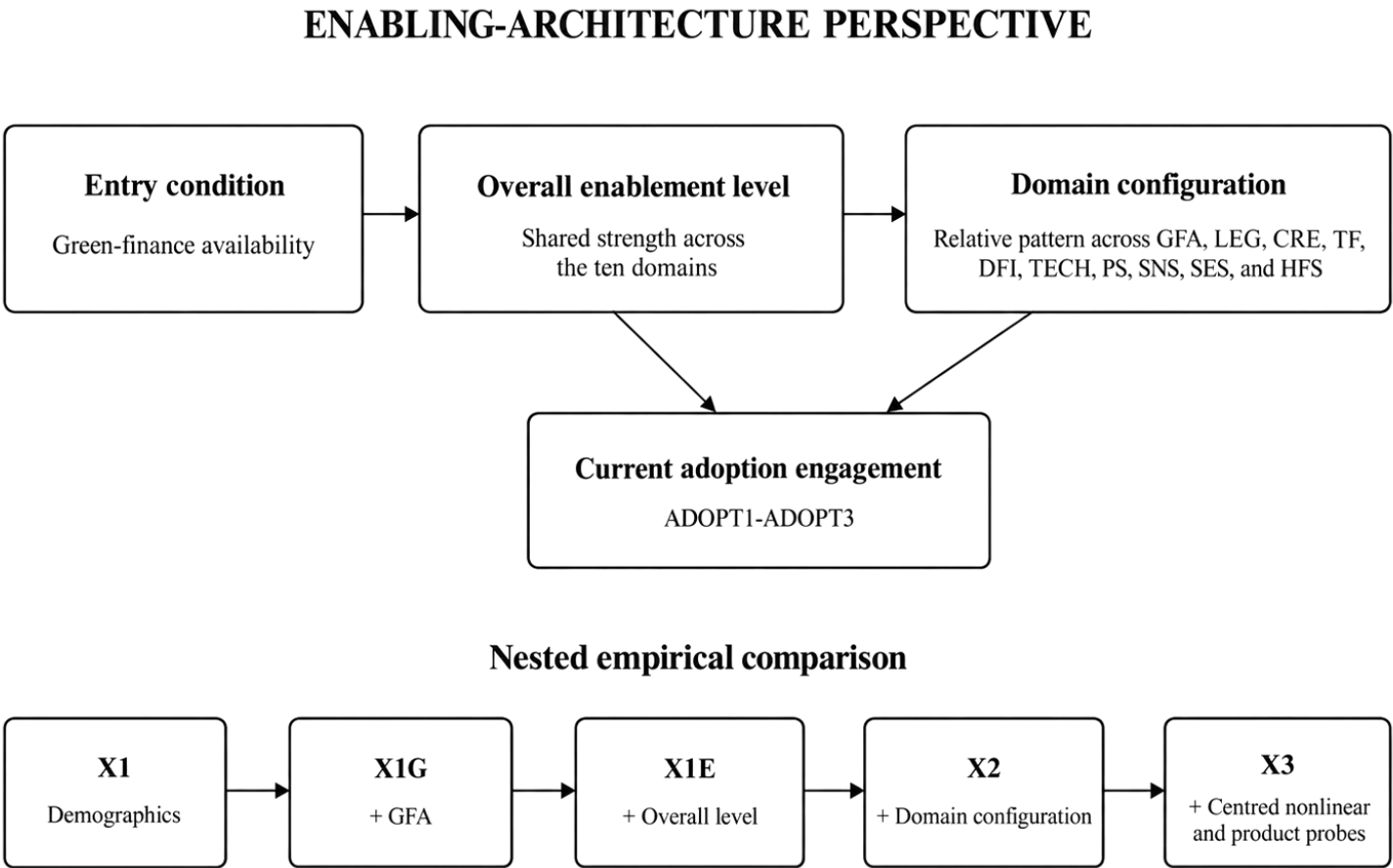


Figure 1

Enabling-architecture framework and nested analytical design. GFA = green-finance availability; LEG = legibility; CRE = credibility; TF = temporal fit; DFI = digital financial inclusion; TECH = technological capability; PS = policy support; SNS = social network support; SES = socioeconomic resources; HFS = household financial stability.

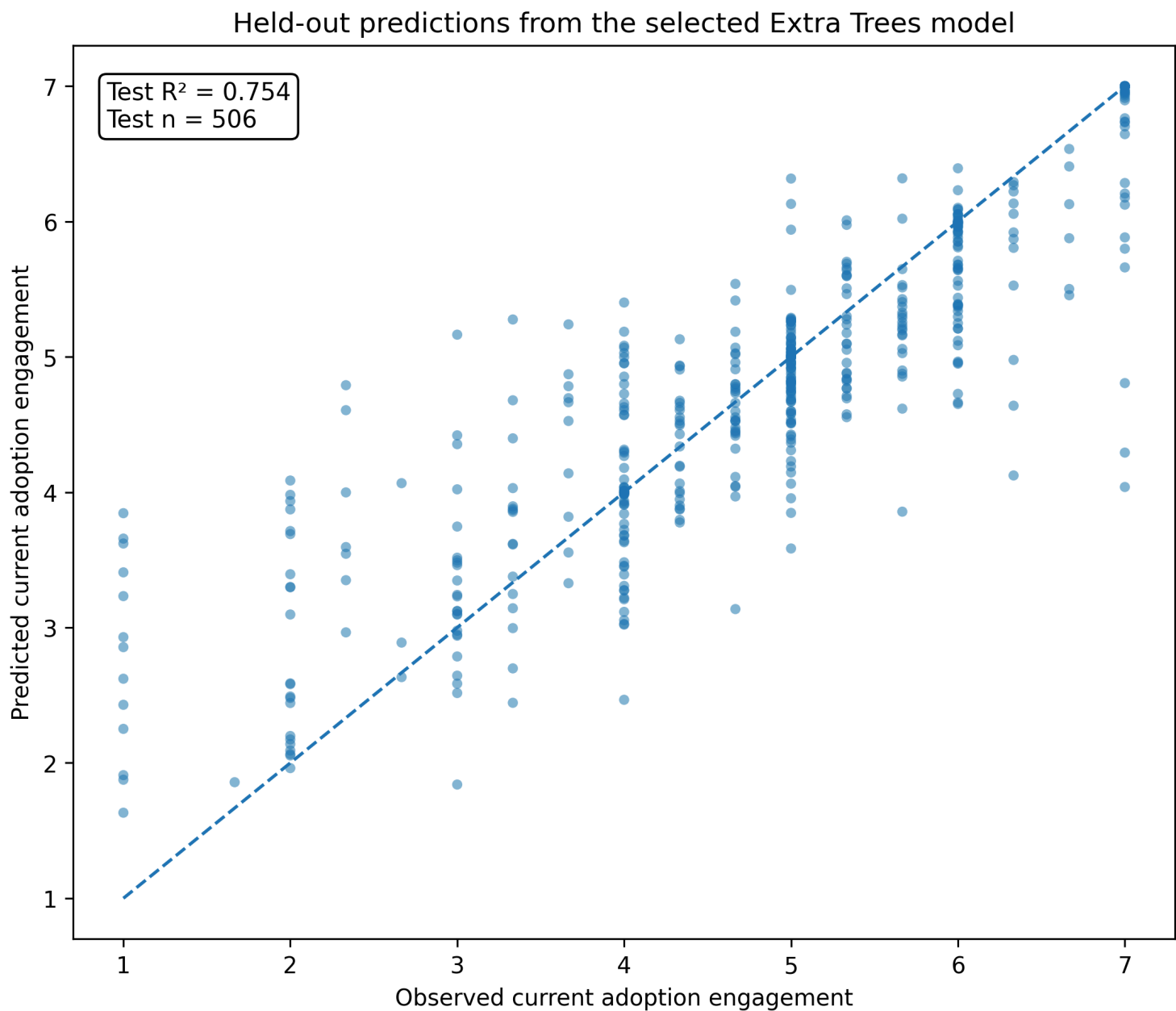


**Figure 2**

Predicted versus observed current adoption engagement in the held-out test set. The diagonal represents perfect prediction. Model selection used training cross-validation before the held-out test set was evaluated.

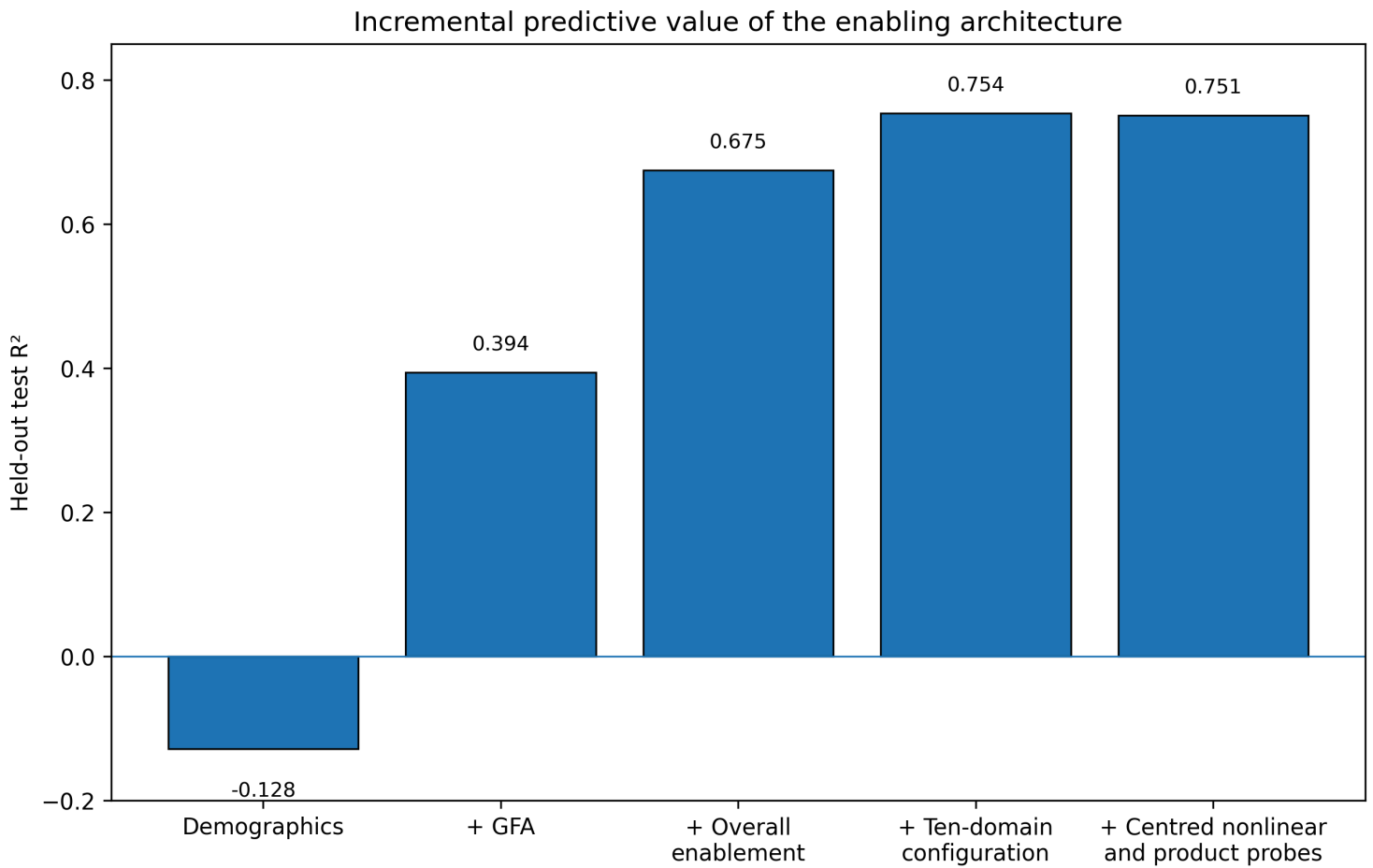


**Figure 3**

Incremental held-out predictive performance across nested feature sets. X1 = demographics; X1G = demographics plus GFA; X1E = demographics plus overall enablement; X2 = demographics plus ten domain scores; X3 = X2 plus centred nonlinear and product probes.

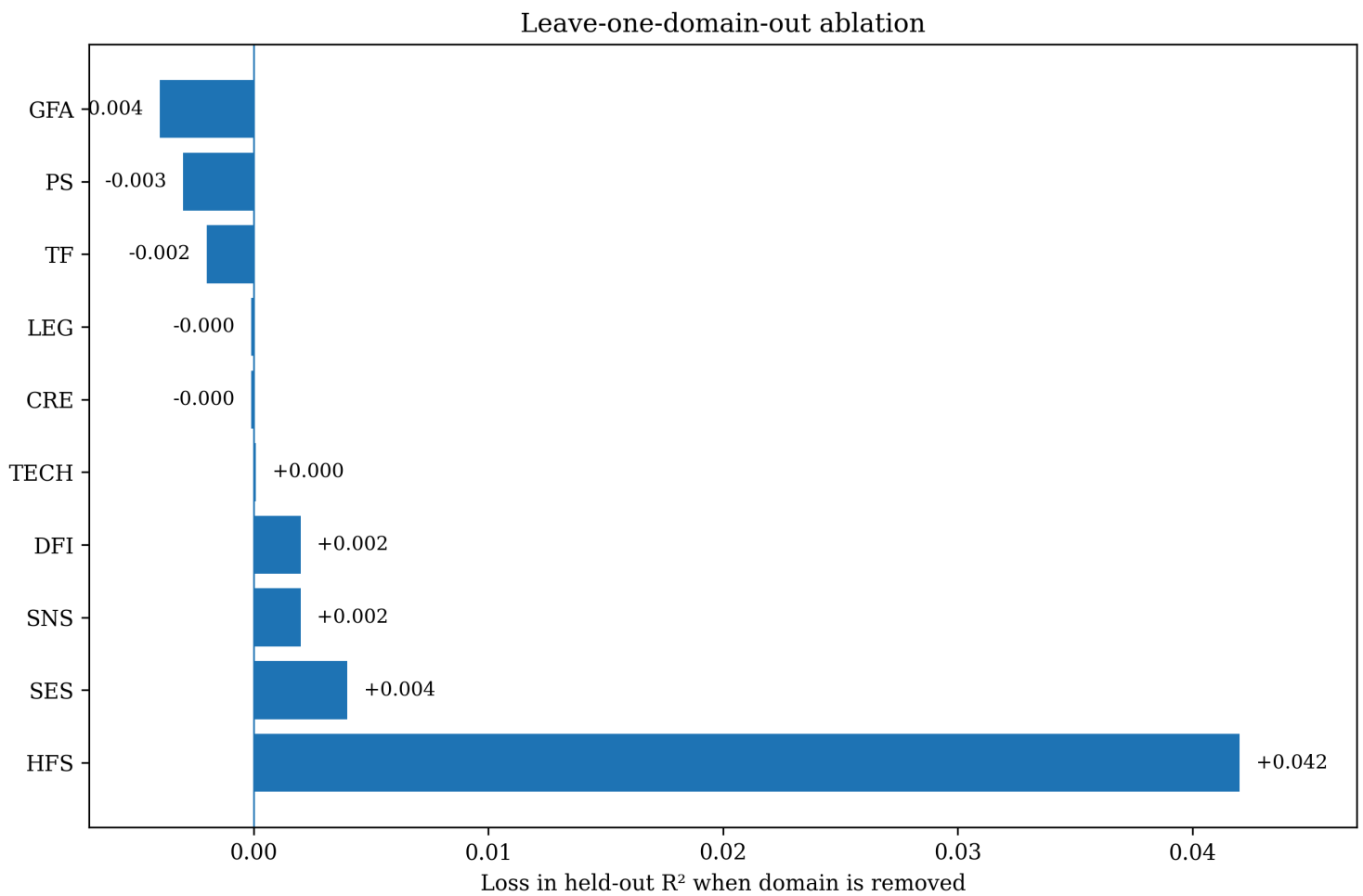


**Figure 4**

Loss in held-out  $R^2$  from leave-one-domain-out ablation. Positive values indicate deterioration when the domain is removed; small negative values indicate negligible improvement after removal.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryData1.xlsx](#)
- [SupportingInstitutionalEthicsDeterminationTDTU.pdf](#)
- [MainManuscriptMARKEDRevision3.docx](#)