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When Digital Access Becomes Investment Capability: Financial Literacy and Portfolio Diversification Across Countries

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Abstract

This study tests whether macro-level conditions corresponding to economic, functional, emotional and social value explain cross-country variation in a digital investment adoption proxy, whether adoption is associated with a broader portfolio-diversification environment, and whether financial-literacy capacity strengthens that conversion.A five-wave panel covering 82 countries and 291 country-year observations is assembled for the 2011, 2014, 2017, 2021 and 2024 Global Findex waves using open World Bank Development Indicators and Global Findex series. Entropy-weighted composite indices are estimated in two-way country and year fixed-effects models with Driscoll–Kraay standard errors. K-means clustering, silhouette validation and ANOVA provide descriptive market typologies.Economic and social value-enabling conditions positively predict adoption, whereas functional and emotional proxies are negative in the within-country specification. Adoption is positively associated with diversification (β=0.049, p=0.008), and its interaction with financial-literacy capacity is positive (β=0.088, p=0.006). Cluster estimates require caution: the mature-market interaction has a larger point estimate but is statistically imprecise (p=0.207), while the low-access estimate is smaller but significant.The paper moves beyond intention-based, single-country digital-banking studies by testing a macro analogue of perceived value, linking adoption to a consequential market outcome and identifying financial literacy as a conversion capability. It also shows where a simple monotonic transfer of micro perceived-value predictions fails under country fixed effects.

Keywords *digital investment adoption; perceived value; digital banking; financial literacy; portfolio diversification*

1. Introduction

Digital financial services have changed how retail customers enter, navigate and remain in formal financial markets. Mobile banking, mobile payments and platform-based financial services can reduce transaction frictions, extend service availability and make financial products reachable at lower marginal cost. The banking literature has therefore devoted substantial attention to why customers accept and continue to use digital channels (Shaikh and Karjaluoto, 2015; Tam and Oliveira, 2017; Flavián et al., 2020; Poromatikul et al., 2020). At the same time, the FinTech literature shows that digitisation is not merely a new distribution channel: it alters the architecture of financial intermediation and the range of services that can be offered to customers at scale (Gomber et al., 2017, 2018). These developments make adoption an important marketing outcome, but they also raise a harder question for bank marketing: does wider digital access translate into better participation in financial markets, or does it simply increase the number of customers who can open and operate accounts?

Customer-value research provides a natural starting point for answering that question. Perceived value reflects an evaluation of benefits relative to sacrifices and can include economic, functional, emotional and social components (Zeithaml, 1988; Sheth et al., 1991; Sweeney and Soutar, 2001; Woodruff, 1997). In digital banking, the same logic appears in studies that connect service quality, design, usefulness, trust, social influence and perceived value to adoption or continuance (Parasuraman and Grewal, 2000; Amin, 2016; Gupta and Arora, 2017; Chaouali et al., 2020). Yet the dominant unit of analysis remains the individual customer, normally observed in one market at one point in time. Consequently, the literature is strong on the psychology of intention and use but weaker on whether country-level environments that make those values feasible are associated with broader digital financial participation across markets.

This creates a substantive complication. A national market can have widespread connectivity but weak financial depth, extensive account ownership but limited investment activity, or improving macroeconomic stability without a corresponding rise in the use of investment-related services. In other words, access, adoption and consequential financial-market participation need not move together. Financial inclusion research similarly demonstrates that the availability of accounts is only one part of participation (Beck et al., 2007; Allen et al., 2016; Sarma and Pais, 2011; Ozili, 2018). Moreover, financial literacy determines whether households understand risk,

seek advice, participate in stock markets and hold diversified portfolios (van Rooij et al., 2011; Lusardi and Mitchell, 2014; von Gaudecker, 2015; Bianchi, 2018). A digital channel may therefore create opportunity without guaranteeing that opportunity is converted into diversified financial behaviour.

A second complication is theoretical. Perceived value is fundamentally a customer-level construct. Directly relabelling macroeconomic indicators as perceptions would create an ecological fallacy. The present study therefore does not claim to measure national 'perceived value'. Instead, it develops a macro analogue in which observable country conditions are treated as value-enabling conditions: income and credit depth represent economic capacity; internet and broadband represent functional access; inflation and credit stability represent the conditions under which emotional security can emerge; and mobile and internet reach represent the diffusion environment underlying social value. This distinction turns the cross-country test into a boundary-condition exercise. If the micro framework scales cleanly, improvements in all four enabling conditions should be positively related to the adoption proxy. If some signs reverse under country fixed effects, the finding limits—not merely confirms—the monotonic transfer of perceived-value theory across levels of analysis.

Accordingly, this study asks three connected questions. First, which economic, functional, emotional and social value-enabling conditions explain within-country change in digital investment adoption across Global Findex waves? Second, is greater adoption associated with a stronger portfolio-diversification environment? Third, does financial-literacy capacity amplify the adoption–diversification link? The analysis uses five Global Findex waves—2011, 2014, 2017, 2021 and 2024—covering 82 countries and 291 country-year observations. Composite indices are constructed by entropy weighting and estimated through two-way fixed-effects models with Driscoll–Kraay standard errors. A k-means typology is used as a descriptive complement rather than as a substitute for the panel analysis.

The study contributes to bank-marketing research in four ways. First, it extends the value conversation from individual perceived benefits to the national conditions that make those benefits deliverable, while explicitly preserving the distinction between perceptions and macro proxies. Second, it shifts the dependent-variable logic from intention or usage alone toward a post-adoption market outcome: portfolio diversification and equity-market breadth. Third, it positions financial literacy as a conversion capability that determines whether digital access becomes more

consequential participation, linking customer education to the effectiveness of digital distribution. Fourth, the fixed-effects design provides a demanding falsification opportunity. The positive economic and social coefficients coexist with negative functional and emotional coefficients, showing that the simple proposition 'more enabling conditions always produce more adoption' is not supported once persistent country differences and common time shocks are removed. This partial failure is theoretically informative and gives banks and regulators a more realistic basis for market sequencing than a universal technology-first prescription.

2. Literature review and hypothesis development

2.1 Perceived value and the macro value-enabling conditions framework

Perceived value has been conceptualised as the customer's overall assessment of utility based on what is received and what is given (Zeithaml, 1988). Consumption-value theory broadens this evaluation beyond price to functional, social and emotional sources of value (Sheth et al., 1991), while later multidimensional scales distinguish price/value-for-money, performance, emotional and social dimensions (Sweeney and Soutar, 2001). Related work emphasises the experiential side of consumption (Holbrook and Hirschman, 1982), hedonic and utilitarian value (Babin et al., 1994), customer assessments of service value (Bolton and Drew, 1991), the dynamic role of customer goals (Woodruff, 1997), and multidimensional service value (Petrick, 2002). Together, these approaches reject the idea that customer adoption can be explained by a single benefit or sacrifice.

Technology changes how these value dimensions are produced. Parasuraman and Grewal (2000) argue that technology reshapes the quality–value–loyalty chain, while mobile-banking research shows that interface design can influence functional, emotional and social value and, through those evaluations, adoption intention (Chaouali et al., 2020). Service-quality evidence similarly connects the performance of internet and e-banking channels to satisfaction and loyalty (Amin, 2016; Shankar and Jebarajakirthy, 2019). This stream supports using perceived value as the theoretical core of a digital-finance adoption model.

The present study nevertheless changes the level of analysis. Country indicators cannot reveal what an individual customer feels. They can reveal whether the environment supplies resources from which particular forms of value are more likely to be realised. We call these macro value-enabling conditions. The approach is analogous rather than isomorphic: it uses perceived-value

theory to organise national conditions, then evaluates whether changes in those conditions are consistent with the direction predicted by the micro theory. This design strengthens the paper's novelty because it permits both corroboration and falsification. Positive signs indicate that a value-enabling condition scales in the predicted direction; null or negative signs identify boundaries to the cross-level translation.

2.2 Economic value-enabling conditions and digital investment adoption

Economic value in financial services reflects affordability, monetary benefit and the reduction of financial sacrifice. At the macro level, income capacity and credit depth condition whether customers can make use of digital financial services beyond basic transactions. Higher income enlarges the feasible set of saving and investment products, while deeper private credit markets indicate a financial system with greater intermediation capacity. The digital-finance literature likewise emphasises lower transaction costs and expanded reach as mechanisms through which technology can make formal finance more attractive (Gomber et al., 2017; Ozili, 2018). Financial inclusion research shows that formal account ownership is systematically related to broader economic and institutional conditions (Allen et al., 2016).

The prediction is therefore straightforward at the enabling-condition level: when a country's economic capacity improves relative to its own history, the attainable economic value of digital finance should improve and adoption should rise.

H1. Economic value-enabling conditions are positively associated with digital investment adoption.

2.3 Functional value-enabling conditions and digital investment adoption

Functional value concerns performance, convenience and the ability of a service to accomplish the customer's task. Technology-acceptance research has long shown that usefulness and ease of use influence acceptance (Davis, 1989), while UTAUT and UTAUT2 emphasise performance expectancy, facilitating conditions and social influence (Venkatesh et al., 2003, 2012). Mobile-banking studies extend this logic to task–technology fit (Zhou et al., 2010), mobile payments (Oliveira et al., 2016), cultural contingencies (Baptista and Oliveira, 2015) and the continued use of banking apps (Poromatikul et al., 2020).

At national scale, internet reach and fixed-broadband availability are observable infrastructure conditions that make functional benefits technically possible. Better infrastructure should reduce connection constraints, improve service reliability and expand the set of digital financial tasks that can be completed remotely. Prior evidence on mobile phones in developing economies further shows how communication infrastructure can alter access to economic information and services (Aker and Mbiti, 2010). Accordingly, a direct macro translation predicts a positive within-country effect.

H2. Functional value-enabling conditions are positively associated with digital investment adoption.

2.4 Emotional value-enabling conditions and digital investment adoption

Emotional value arises when use generates positive feelings or reduces anxiety. In financial services, uncertainty, risk and trust are central because adoption requires customers to expose money and personal information to an institutional and technological system. Perceived-risk research shows that risk facets suppress e-service adoption (Featherman and Pavlou, 2003), while trust can complement technology-acceptance mechanisms (Gefen et al., 2003). Mobile-banking studies similarly identify trust, risk and flow experience as relevant to acceptance (Luo et al., 2010; Zhou, 2012).

A country-level analogue cannot observe anxiety directly. It can, however, capture macro-financial stability conditions that make reassurance more or less plausible. Lower inflation and deeper, more stable private credit conditions should reduce background financial uncertainty and thereby raise the potential emotional value of engaging with financial services. Under a simple cross-level translation, improvements in stability should therefore support adoption.

H3. Emotional value-enabling conditions are positively associated with digital investment adoption.

2.5 Social value-enabling conditions and digital investment adoption

Social value reflects benefits generated through belonging, approval, communication and network visibility. The importance of social influence is explicit in UTAUT (Venkatesh et al., 2003) and appears repeatedly in mobile-banking and mobile-payment studies (Oliveira et al., 2016; Flavián et al., 2020). Communication channels also shape mobile-banking beliefs and usage

intention because customers learn about financial technologies from banks, peers and media (Tran and Corner, 2016).

At the macro level, dense mobile subscriptions and internet reach increase the number of potential adopters who can observe, discuss and recommend digital services. Network diffusion can also lower perceived novelty by making platform use socially ordinary. Evidence from mobile money demonstrates that networked financial technologies can change transaction and risk-sharing behaviour when use becomes embedded in communities (Jack and Suri, 2014; Suri and Jack, 2016). These mechanisms support a positive relation between social diffusion conditions and adoption.

H4. Social value-enabling conditions are positively associated with digital investment adoption.

2.6 From adoption to portfolio diversification

Adoption matters strategically only if it changes what customers can do. Digital channels lower search and transaction costs, enable more frequent account access and can expand exposure to financial products. FinTech thus potentially moves customers from basic access toward broader participation (Gomber et al., 2018). Formal financial access is also associated with development of the banking system and market reach (Beck et al., 2007; Sarma and Pais, 2011).

Household-finance research shows, however, that participation and diversification are demanding outcomes. Limited participation can arise from information, trust and fixed-cost frictions (Campbell, 2006; Guiso et al., 2008). The macro diversification index used here—market capitalisation, trading activity, turnover and listed firms—is therefore interpreted as a national portfolio-diversification environment rather than a direct measure of a particular household's portfolio. If digital adoption broadens engagement with formal financial services, increases the pool of market participants and lowers access frictions, an improvement in the adoption proxy should be associated with an improvement in this market-level diversification environment.

H5. Digital investment adoption is positively associated with the portfolio-diversification environment.

2.7 Financial literacy as a conversion capability

Financial literacy provides the knowledge needed to evaluate products, understand risk–return trade-offs and act on financial information (Lusardi and Mitchell, 2014). It is closely linked to

stock-market participation (van Rooij et al., 2011; Sivaramakrishnan et al., 2017), portfolio diversification (Abreu and Mendes, 2010; von Gaudecker, 2015), portfolio dynamics and rebalancing (Bianchi, 2018), and the demand for financial advice (Calcagno and Monticone, 2015). This literature implies that access and capability are complements: a platform can present options, but customers need sufficient knowledge to evaluate and combine them.

The literature also cautions against assuming that education automatically changes downstream behaviour. The effects of financial education depend on design and context (Fernandes et al., 2014; Hastings et al., 2013; Kaiser and Menkhoff, 2017), and empirical work finds meaningful heterogeneity in the relationship between literacy and financial behaviour (Grohmann, 2018; Stolper and Walter, 2017). In the present macro framework, financial-literacy capacity is therefore treated as an amplifying resource: it should increase the extent to which adoption is converted into a stronger diversification environment, rather than serving only as an independent antecedent of adoption.

H6. Financial-literacy capacity positively moderates the relationship between digital investment adoption and the portfolio-diversification environment.

2.8 Novelty and theoretical boundary conditions

The novelty of the model lies in its sequence and level of analysis. Existing digital-banking studies commonly explain intention, initial use, continuance or loyalty. The present framework instead links four value-enabling conditions to adoption and then links adoption to a consequential market outcome. It simultaneously asks whether a customer-value logic survives when moved from perceptions to country-level conditions. That makes non-support theoretically useful: H1–H4 are not merely predictive hypotheses but tests of whether the expected direction of perceived-value effects is preserved after country and year fixed effects remove persistent cross-country level differences.

This boundary-condition logic also prevents overclaiming. A significant macro proxy does not prove that an individual customer perceived the corresponding value, and a negative macro coefficient does not establish that functional or emotional value harms adoption at the individual level. Rather, the coefficient asks whether a country that improves on the selected enabling indicators also experiences a within-country change in the adoption proxy, conditional on the other

value blocks and common time shocks. The discussion returns to this distinction when interpreting the negative functional and emotional coefficients.

3. Research method

3.1 Research design, sample and data alignment

The study uses a macro-comparative longitudinal design. The unit of analysis is the country-year observed at a Global Findex wave. The panel covers five waves—2011, 2014, 2017, 2021 and 2024—and contains 291 country-year observations for 82 countries. All indicators are taken from open World Bank Development Indicators (WDI) and Global Findex series, with telecommunications indicators originating from WDI/ITU series. Annual market and infrastructure indicators are aligned to each Findex wave. When an exact wave-year observation is unavailable, the nearest observation within ±1 year is used; no observations are simulated.

The design is unbalanced because not every country has complete information in every wave. This is preferable to filling missing country-years with model-generated values, which could mechanically strengthen time trends. Country and year fixed effects subsequently absorb time-invariant country characteristics and common wave shocks. The resulting coefficients are therefore interpreted as within-country associations rather than cross-sectional comparisons of high- versus low-income countries.

3.2 Construct operationalisation

Table I maps each theoretical construct to the indicators available in the open international datasets. Importantly, ECON, FUNC, EMO and SOC are macro value-enabling proxies, not psychometric measurements of perceived value. DIA is an adoption/access proxy derived from account ownership and account ownership among the poorest 40 per cent, not a direct count of transactions on investment apps. DIV measures the national diversification environment through equity-market breadth and activity, while FL is a financial-literacy-capacity proxy based on private credit depth, inverted youth dependency and internet reach. These distinctions are retained throughout the interpretation to avoid a cross-level measurement claim that the source data cannot support.

Table I. Construct-to-proxy mapping and data sources

Construct	Country-level proxy indicators	Source
Economic value (ECON)	GDP per capita (constant); domestic credit to private sector (% GDP)	WDI
Functional value (FUNC)	Individuals using internet (%); fixed broadband subscriptions	WDI/ITU
Emotional value (EMO)	Inflation (inverted); private-credit depth (stability)	WDI
Social value (SOC)	Mobile-cellular subscriptions; internet reach	WDI/ITU
Digital Investment Adoption (DIA)	Account ownership (%); account ownership poorest-40%	Global Findex
Portfolio Diversification (DIV)	Market capitalisation (% GDP); stocks traded (% GDP); turnover; listed firms	WDI
Financial Literacy (FL, proxy)	Private-credit depth; youth dependency (inverted); internet	WDI

3.3 Entropy-weighted composite construction

Indicators are first transformed so that larger values consistently represent more of the underlying construct. Benefit indicators are min–max normalised, whereas cost indicators such as inflation and youth dependency are directionally inverted before normalisation. For indicator j in observation i,t, the generic benefit normalisation is:

$$z_{ijt} = (x_{ijt} - \min(x_j)) / (\max(x_j) - \min(x_j)) \quad (1)$$

Entropy weighting then assigns more weight to indicators that contain greater cross-observation information. Let $p_{ijt} = z_{ijt} / \Sigma_{it} z_{ijt}$. With K equal to the number of usable country-year observations for the indicator, entropy is $e_j = -[1/\ln(K)]\Sigma_{it} p_{ijt} \ln(p_{ijt})$. The information utility is $d_j = 1 - e_j$, the

weight is $w_j = d_j/\Sigma_j d_j$, and each composite is $C_{it} = \Sigma_j w_j z_{ijt}$. This data-driven rule avoids assigning equal or judgemental weights to indicators with very different dispersion. The approach does not, however, solve conceptual overlap among indicators; that issue is evaluated when the correlation matrix is interpreted.

3.4 Panel equations and hypothesis tests

The first model tests H1–H4 using two-way fixed effects. Country effects μ_i remove all time-invariant national characteristics, while wave effects τ_t remove common shocks affecting the full sample. The estimating equation is:

$$DIA_{it} = \beta_0 + \beta_1 ECON_{it} + \beta_2 FUNC_{it} + \beta_3 EMO_{it} + \beta_4 SOC_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (2)$$

H1–H4 are evaluated from the sign and statistical significance of β_1–β_4. DIA is standardised in the adoption model. Because the value blocks are correlated composites, the coefficients are interpreted as conditional within-country effects rather than as isolated causal effects of a single indicator.

The second model tests H5 and H6. Adoption and the financial-literacy-capacity proxy are standardised before the interaction term is formed. Urbanisation enters as a control in the diversification specification. The equation is:

$$DIV_{it} = \alpha_0 + \alpha_1 DIA_{it} + \alpha_2 FL_{it} + \alpha_3 (DIA_{it} \times FL_{it}) + \alpha_4 \ln(URB_{it}) + \mu_i + \tau_t + u_{it} \quad (3)$$

H5 is supported when α_1 is positive and significant. H6 is supported when α_3 is positive and significant. The interaction is interpreted as whether financial-literacy capacity changes the within-country association between adoption and the diversification environment, not as evidence that every literate individual diversifies more.

3.5 Inference, clustering and RStudio analytical workflow

The panel models use Driscoll–Kraay standard errors to address heteroskedasticity, serial correlation and general cross-sectional dependence in the disturbance process (Driscoll and Kraay, 1998). Hoechle (2007) provides a practical panel implementation and discusses finite-sample behaviour under cross-sectional dependence. Because the panel contains only five Findex waves, statistical inference should still be read with appropriate caution: Driscoll–Kraay consistency is

asymptotic in the time dimension, so coefficient direction, effect size and consistency across analyses are as important as mechanical p-value thresholds.

Country typologies are generated through k-means clustering using the adoption-related composites. K-means partitions observations by minimising within-cluster dispersion (Hartigan and Wong, 1979). The number of clusters is selected using the average silhouette width, which evaluates cohesion and separation (Rousseeuw, 1987). The selected two-cluster solution has a silhouette value of 0.478. ANOVA is then used as a descriptive validation that construct means differ across the derived groups. Finally, the diversification model is re-estimated by cluster to explore heterogeneity. These subgroup models are interpreted descriptively because they split an already limited panel and do not constitute a formal coefficient-difference test.

All data preparation, composite construction, panel estimation, interaction analysis, clustering and figure production were conducted in the R environment through RStudio. The analytical toolchain therefore consists of entropy weighting, two-way fixed-effects regression, Driscoll–Kraay covariance estimation, k-means clustering, silhouette diagnostics, ANOVA, simple-slope visualisation and geospatial mapping. For reproducibility, the exact R, RStudio and package versions used in the final analytical run should be preserved with the replication archive.

4. Results and analysis

4.1 Descriptive statistics, correlations and adoption trend

Table II reports the distributions of the seven composite indices. DIA has the highest mean (0.667) and substantial dispersion (SD=0.272), indicating that the panel includes countries with very low and very high levels of the adoption proxy. DIV has a low mean (0.071) and a long upper tail (maximum=0.986), consistent with the concentration of deep and active equity markets in a relatively small set of countries. The spread of ECON, FUNC, EMO, SOC and FL is sufficient to support within-panel comparison, although the bounded composite construction means that magnitudes are index-specific rather than interpretable in original units.

Table II. Descriptive statistics (N = 291 country-years; 82 countries)

Construct	*Mean*	*SD*	*Min*	*Max*
ECON	*0.360*	*0.175*	*0.089*	*0.936*

FUNC	*0.400*	*0.210*	*0.009*	*0.816*
EMO	*0.300*	*0.198*	*0.039*	*1.000*
SOC	*0.525*	*0.177*	*0.048*	*0.860*
DIA	*0.667*	*0.272*	*0.053*	*1.000*
DIV	*0.071*	*0.090*	*0.006*	*0.986*
FL	*0.489*	*0.174*	*0.060*	*0.975*

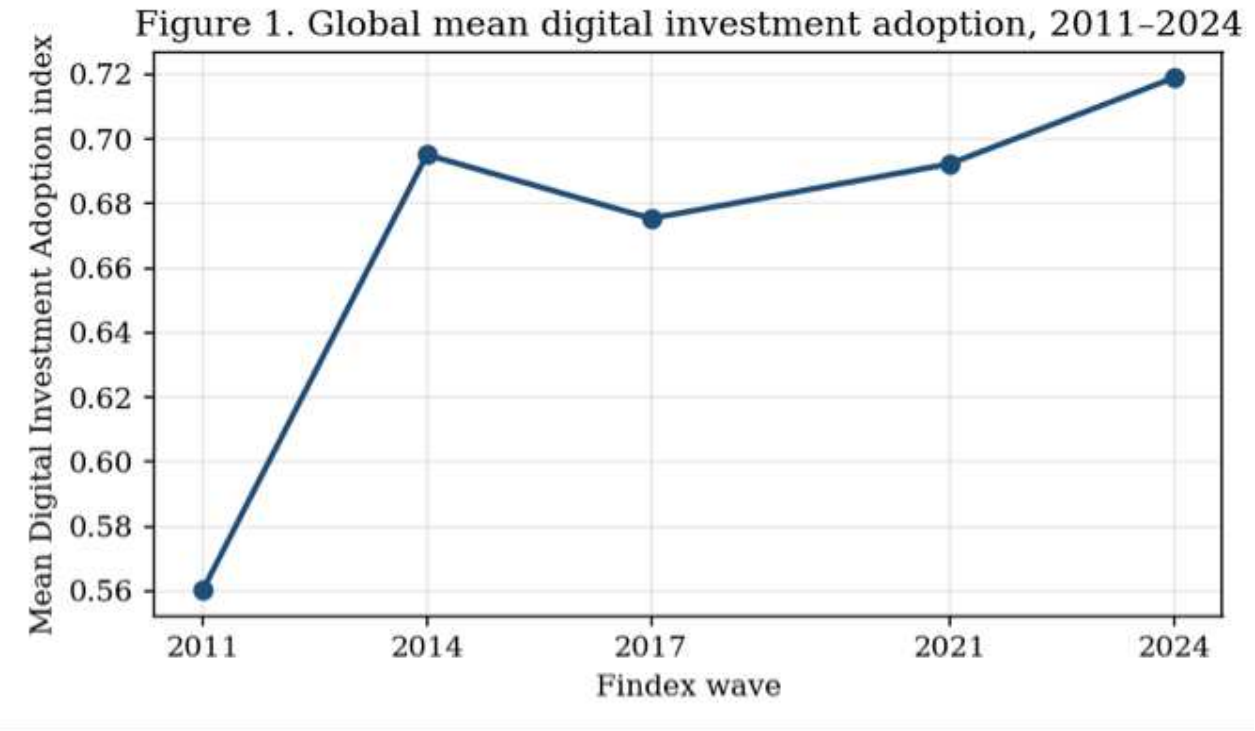
Table III shows strong positive pooled correlations among several enabling-condition composites. ECON correlates 0.98 with EMO and 0.91 with FL; FUNC correlates 0.88 with SOC and 0.82 with FL. These values are substantively important. They indicate that national development conditions co-move and that some composites share underlying indicators, including private credit and internet reach. The fixed-effects regressions therefore estimate partial within-country associations under substantial conceptual overlap. The correlation pattern does not invalidate the model, but it rules out an interpretation in which each coefficient is treated as a fully independent structural effect.

Table III. Pearson correlation matrix

	ECON	**FUNC**	**EMO**	**SOC**	**DIA**	**DIV**	**FL**
ECON	1.00	0.63	0.98	0.54	0.64	0.59	0.91
FUNC		1.00	0.50	0.88	0.77	0.26	0.82
EMO			1.00	0.43	0.54	0.61	0.86
SOC				1.00	0.66	0.25	0.82
DIA					1.00	0.27	0.73
DIV						1.00	0.50
FL							1.00

Figure 1 traces the global mean DIA index across the five waves. The mean rises sharply from 2011 to 2014, softens in 2017 and then resumes an upward trajectory through 2021 and 2024. The

pattern suggests that digital/financial access expanded over the period but not monotonically at every wave. Because the figure reports an unconditional global mean, it is descriptive and should not be used to infer the effect of any one value-enabling condition.



4.2 Bivariate patterns and the multivariate adoption model (H1–H4)

Figure 2 displays the bivariate associations between each value-enabling proxy and DIA. All four panels show an upward unconditional pattern, especially for ECON, FUNC and SOC. This visual evidence is useful precisely because it contrasts with the fixed-effects estimates: the pooled country differences suggest that countries with stronger infrastructure and stability tend to have higher adoption, whereas the within-country model asks whether marginal change in those same factors predicts additional adoption after country and wave effects and the other value blocks are controlled.

Figure 2. Perceived-value proxies and digital investment adoption

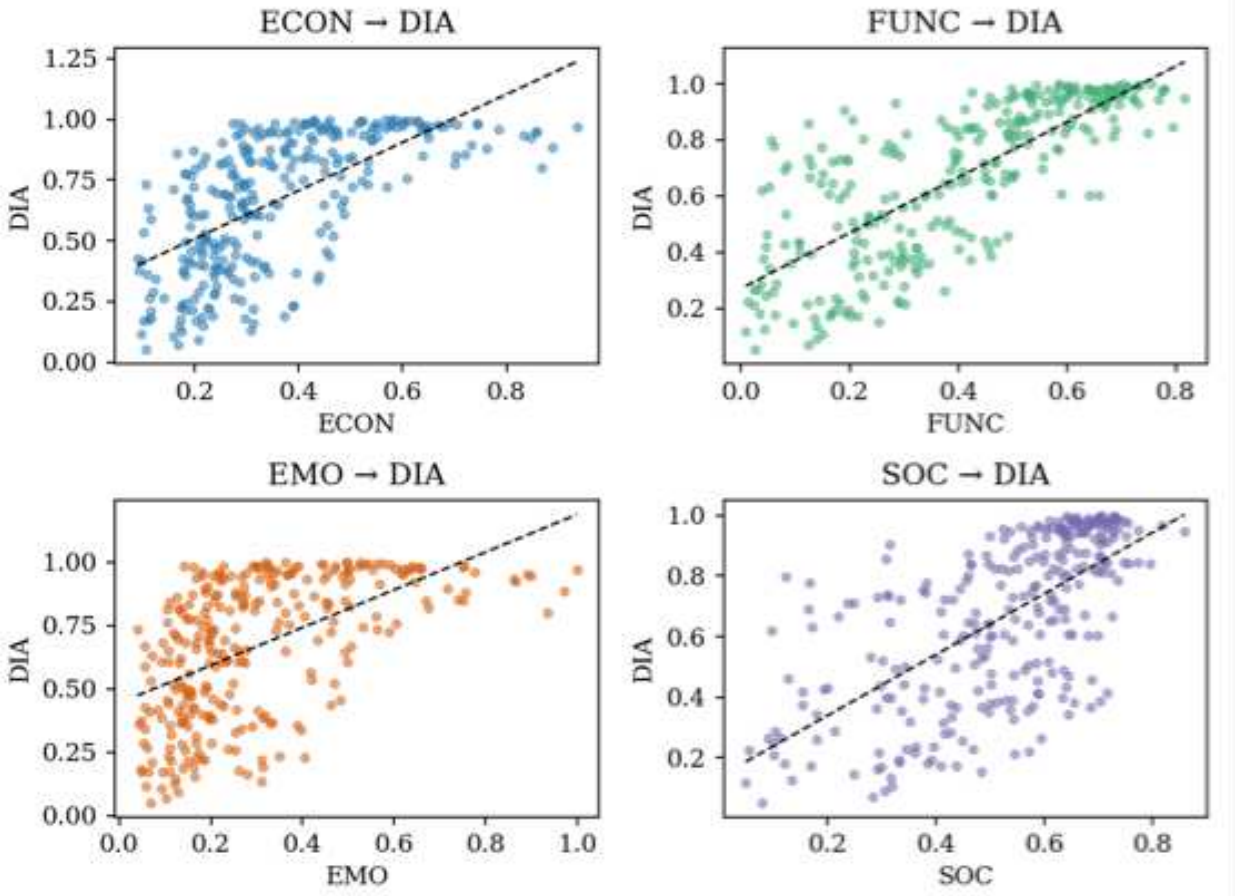


Table IV reports the two-way fixed-effects adoption model. Economic value-enabling conditions are positive and statistically significant (β=1.854, SE=0.378, p<0.001), supporting H1. Social value-enabling conditions are also positive (β=0.448, SE=0.098, p<0.001), supporting H4. Together, these results indicate that within-country gains in economic capacity and network diffusion are associated with increases in the adoption proxy even after persistent national differences and common wave shocks are absorbed.

The functional coefficient is negative (β=−0.217, SE=0.084, p=0.011), so H2 is not supported. The emotional-stability proxy is also negative and significant (β=−1.459, SE=0.315, p<0.001), so H3 is not supported. These signs should not be translated into the individual-level claim that usefulness, infrastructure or emotional value reduce digital adoption. Rather, they show that the expected positive cross-level translation does not survive the conditional within-country specification. The high pooled correlations in Table III and the shared ingredients across

composites make suppression and overlapping development trajectories plausible statistical mechanisms. Theoretically, the result is a boundary condition: infrastructure and stability may be necessary background conditions whose cross-country level differences matter, while incremental gains within already-observed countries do not independently add to adoption once economic capacity and social diffusion are modelled simultaneously. The model explains 56.0 per cent of within-country variation in the standardised adoption proxy (within R^2=0.560).

Table IV. Two-way fixed-effects model — dependent variable: Digital Investment Adoption (standardised)

Predictor	Coef.	Std. err.	t	p
Economic value	1.854	0.378	4.90	<0.001
Functional value	−0.217	0.084	−2.58	0.011
Emotional value	−1.459	0.315	−4.63	<0.001
Social value	0.448	0.098	4.58	<0.001
Within R^2	0.560			
N (country-years)	291			

4.3 Adoption, diversification and financial-literacy moderation (H5–H6)

Table V presents the diversification model. DIA is positive and statistically significant (β=0.049, SE=0.018, t=2.66, p=0.008), supporting H5. The financial-literacy-capacity proxy also has a positive main effect (β=0.147, SE=0.055, p=0.008). Most importantly, the DIA×FL interaction is positive (β=0.088, SE=0.031, t=2.81, p=0.006), supporting H6 in the full panel. Urbanisation is not significant (β=0.067, p=0.582). The within R^2 of 0.069 is modest, which is unsurprising for a market-level diversification outcome shaped by many institutional, regulatory and capital-market factors that are not included in the parsimonious model.

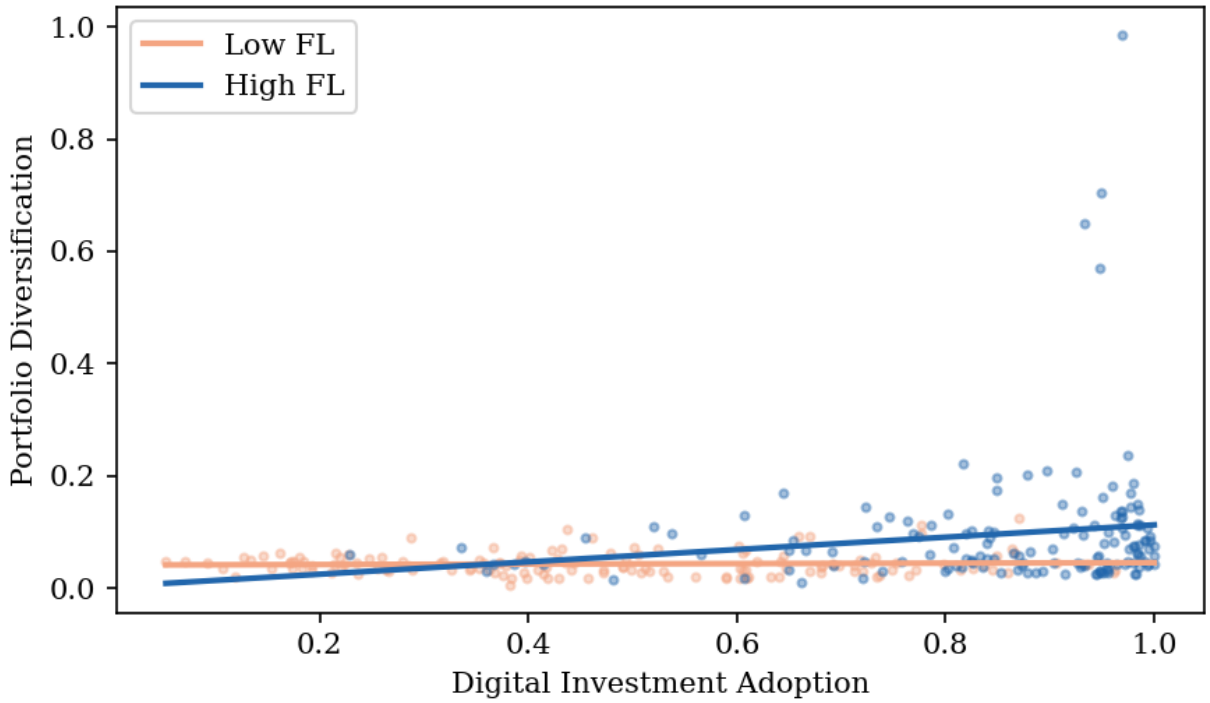
Predictor	*Coef.*	*Std. err.*	*t*	*p*
Digital Investment Adoption	*0.049*	*0.018*	*2.66*	*0.008*
Financial Literacy	*0.147*	*0.055*	*2.66*	*0.008*

Predictor	*Coef.*	*Std. err.*	*t*	*p*
Adoption × Financial Literacy	*0.088*	*0.031*	*2.81*	*0.006*
Urbanisation (ln)	*0.067*	*0.121*	*0.55*	*0.582*
Within R²	*0.069*			
N (country-years)	*291*			

Table V. Two-way fixed-effects model — dependent variable: Portfolio Diversification (standardised)

Figure 3 illustrates the interaction by plotting the adoption–diversification relation at lower and higher levels of FL. The higher-literacy line is steeper, visually matching the positive interaction term. The figure is an illustration of the fitted moderation and not an independent test. Taken together with Table V, it supports a conversion-capability interpretation: expanding digital adoption is more strongly associated with the diversification environment where the capacity to understand and use financial information is greater.

Figure 3. Moderation of financial literacy



4.4 Country typologies and heterogeneity

The k-means analysis selects two clusters with an average silhouette of 0.478. Table VI reports ANOVA comparisons for the seven constructs. All mean differences are statistically significant at $p<0.001$. The largest F statistics occur for DIA (416.80), FL (310.04), ECON (306.35) and FUNC (298.50), indicating that the typology primarily separates countries on adoption/access, literacy-capacity and development/infrastructure dimensions. Because k-means is constructed from these same features, the ANOVA should be interpreted as descriptive validation of separation rather than as an out-of-sample causal test.

Table VI. ANOVA of constructs across country clusters

Construct	*F*	*p*
DIA	*416.80*	*<0.001*
DIV	*24.29*	*<0.001*
FL	*310.04*	*<0.001*
ECON	*306.35*	*<0.001*
FUNC	*298.50*	*<0.001*
EMO	*194.77*	*<0.001*
SOC	*116.33*	*<0.001*

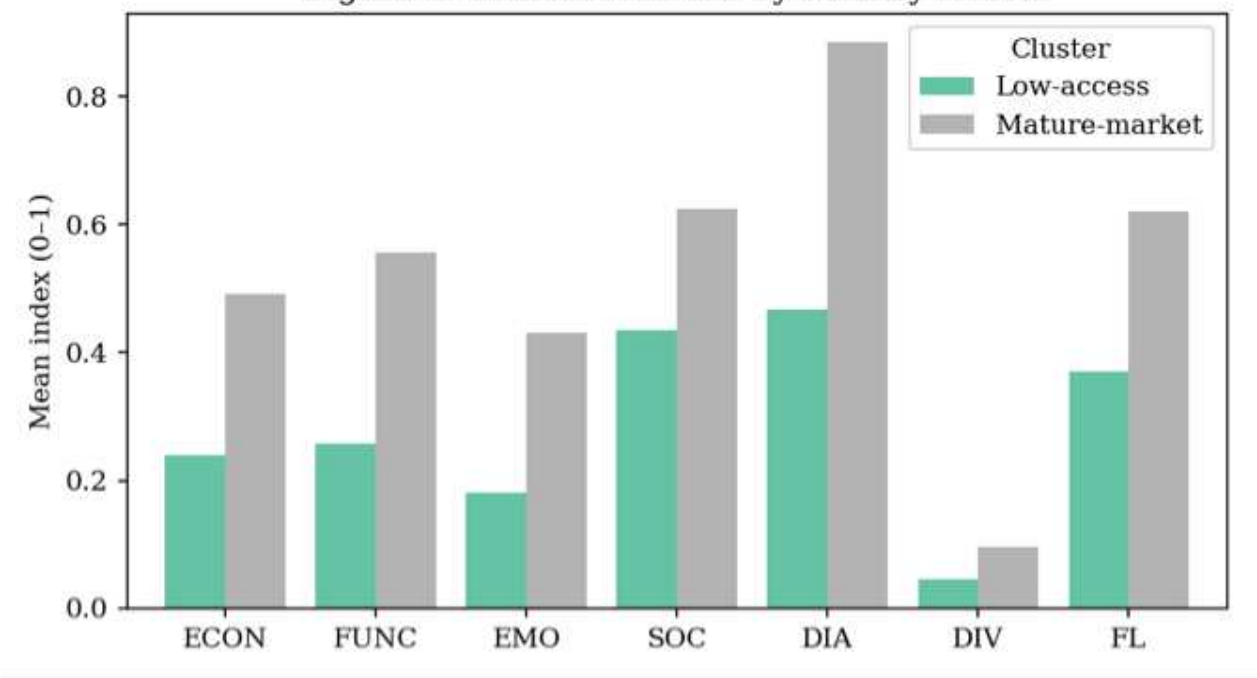
Table VII then re-estimates the interaction by cluster. The mature-market group has a much larger point estimate for DIA×FL (β=0.563) but the estimate is not statistically significant (p=0.207; N=139 country-years). The low-access group has a smaller interaction coefficient (β=0.048) that is statistically precise (p<0.001; N=152). This distinction corrects a potentially misleading reading based only on coefficient magnitude. The evidence does not establish that moderation is statistically stronger in mature markets. It shows a large but imprecise mature-market estimate and a small but statistically reliable low-access estimate. A formal cross-cluster coefficient-difference test would be required before claiming that the moderation effect differs significantly between the two market types.

Table VII. Interaction by Cluster

Cluster	*N*	*Adoption × FL*	*p*	*Within R²*
Mature-market	*139*	*0.563*	*0.207*	*0.123*
Low-access	*152*	*0.048*	*<0.001*	—

Figure 4 plots construct means by cluster and makes the descriptive distinction intuitive. The mature-market group is higher on every displayed construct, with especially large gaps in DIA, FL, ECON and FUNC. DIV remains low in absolute index terms in both groups, which helps explain why the diversification regressions have more limited within variation than the adoption model.

Figure 4. Construct means by country cluster



4.5 Spatial patterns

Figure 5 maps country means for ECON, FUNC, EMO, SOC, FL and DIA. Higher values are visibly concentrated in many high-income economies in North America, Western Europe and parts of East Asia–Pacific, while DIA is more geographically dispersed than several enabling-condition indices. The maps reinforce the reason for using fixed effects: strong spatial level differences can dominate pooled associations, whereas the panel models focus on change within countries.

Figure 5. Global distribution of adoption-related constructs (country means, 2011-2024)

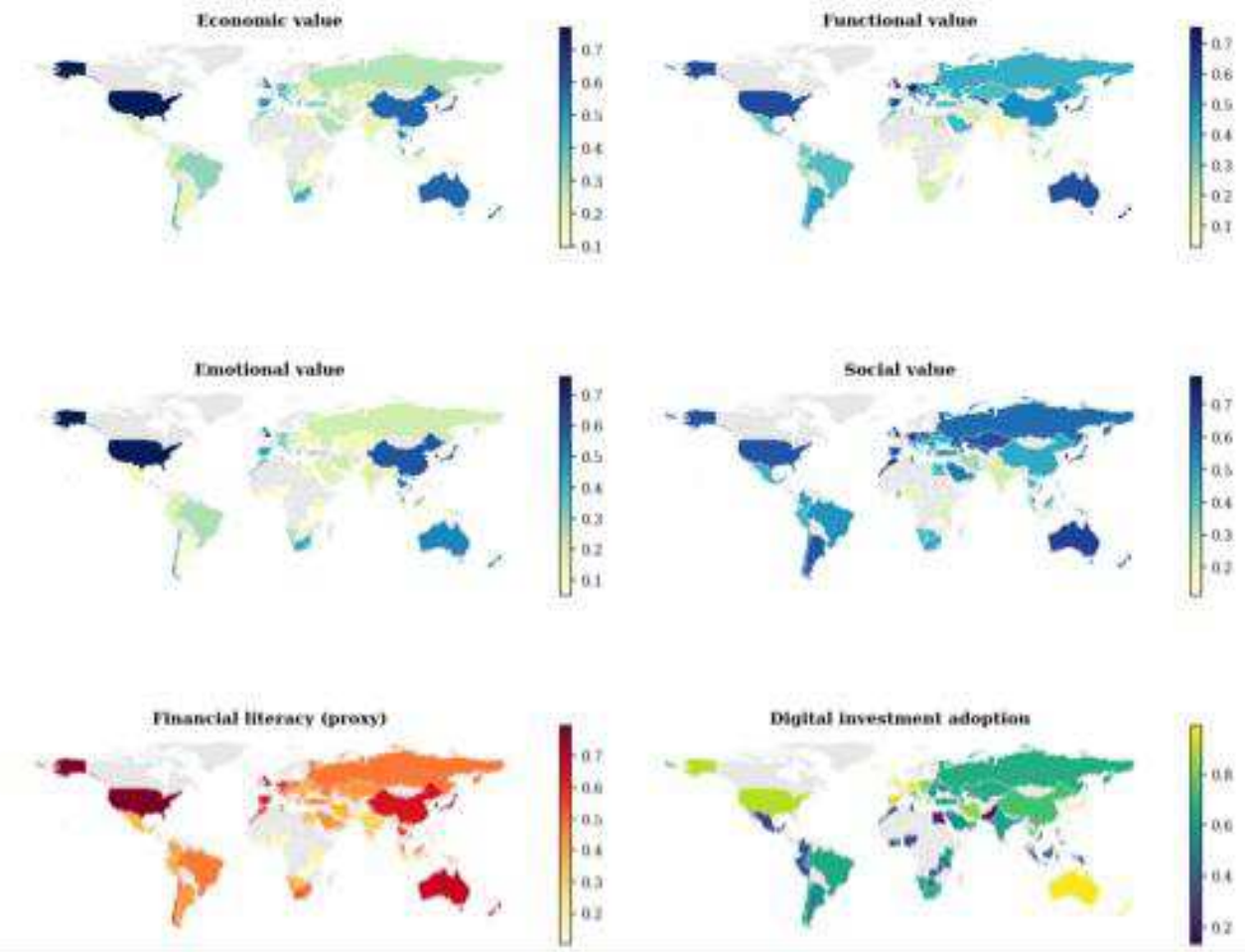


Figure 6 focuses on the country-mean DIA index. The distribution shows high adoption in several advanced economies but also substantial progress across a broader set of emerging markets. The visual pattern is consistent with the full-panel evidence that social diffusion and economic capacity matter, but the map itself is not a hypothesis test and cannot separate the effects of correlated development conditions.

Figure 6. Global map of digital investment adoption

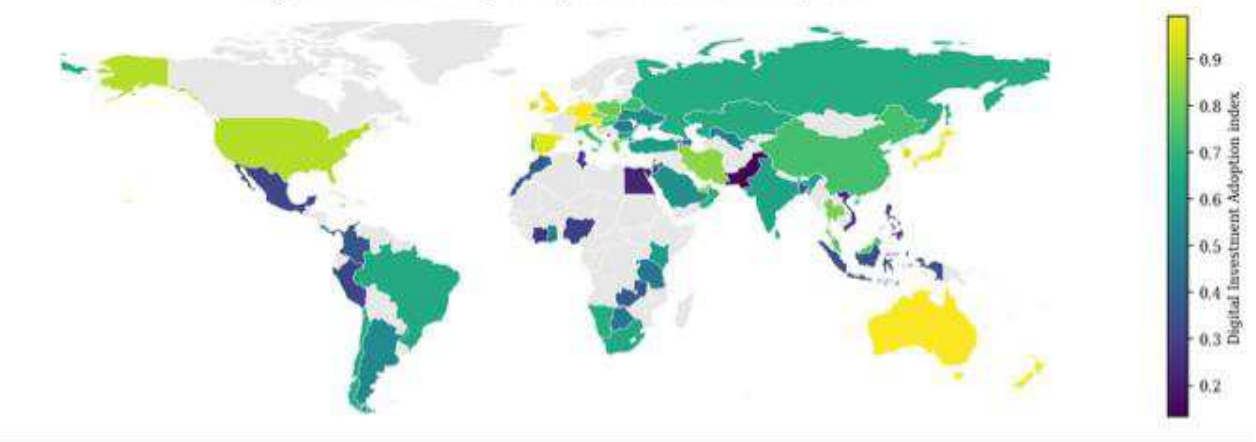
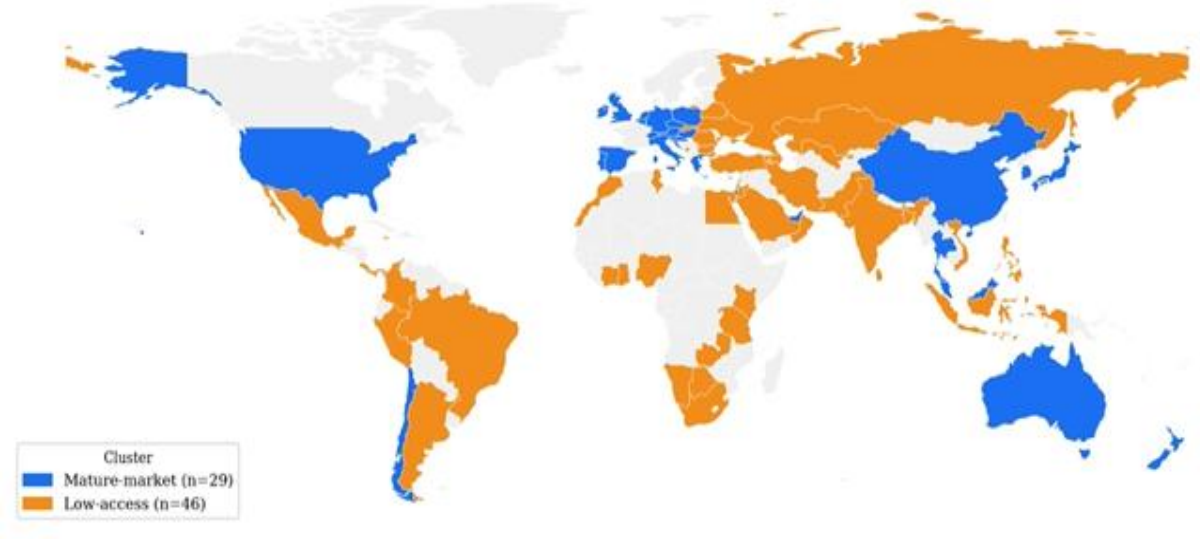


Figure 7 maps the two-cluster typology. The mapping output labels 29 mature-market countries and 46 low-access countries, for 75 mapped countries, whereas the regression panel contains 82 countries. The figure is therefore treated as a descriptive geospatial display of the mapping output rather than a complete census of all estimation units. The cluster-regression sample sizes in Table VII refer to country-year observations (139 and 152, respectively), not to the number of countries displayed on the map. This distinction should be retained in any interpretation of geographic coverage.

Figure 7. K-means country typology of digital investment development



5. Discussion

5.1 Theoretical contributions

The first theoretical contribution is to reposition perceived value as a framework for organising macro enabling conditions without pretending that country indicators are individual perceptions. Classic value theory predicts that customers adopt when benefits outweigh sacrifices and that value has economic, functional, emotional and social components (Zeithaml, 1988; Sheth et al., 1991; Sweeney and Soutar, 2001). The cross-country results partially reproduce that logic: economic and social enabling conditions are positively related to adoption. Economic capacity determines whether customers have resources to participate, while social diffusion expands the network in which digital financial behaviour becomes visible, learnable and normal. These findings connect bank-marketing value theory to the broader financial-inclusion evidence that formal participation depends on both access and the surrounding economic system (Allen et al., 2016; Ozili, 2018).

The second contribution is a theoretically meaningful falsification. Functional and emotional enabling conditions do not retain the expected positive sign under two-way fixed effects. This matters because much digital-banking research implicitly treats connectivity, usefulness, trust and reduced risk as universally monotonic drivers. At the individual level, there is strong support for usefulness, facilitating conditions, trust and perceived risk (Davis, 1989; Venkatesh et al., 2003; Luo et al., 2010; Zhou et al., 2010). The present result does not contradict those customer-level mechanisms. It shows that a macro translation is conditional: once persistent national differences,

wave shocks and correlated development blocks are absorbed, marginal infrastructure and stability improvements do not independently track additional adoption in the expected direction. Thus, perceived-value theory should not be 'scaled up' by simply substituting country indicators for survey measures. The level of analysis changes the theoretical meaning of the variables.

The third contribution is to move beyond adoption as an endpoint. Much of the mobile-banking literature is organised around intention, initial use or continuance (Shaikh and Karjaluoto, 2015; Gupta and Arora, 2017; Flavián et al., 2020; Poromatikul et al., 2020). The positive DIA coefficient in Table V links adoption to a market-level diversification environment. This does not establish that a particular customer becomes diversified because an account is opened; the DIV index is a national market outcome. It does, however, provide evidence that adoption and market breadth/activity move together within countries after fixed effects. This outcome-based extension is important for bank marketing because digital customer acquisition is strategically valuable when it deepens customers' financial participation rather than only migrating transactions from branch to screen.

The fourth contribution is to specify financial literacy as a conversion capability. The positive full-panel interaction is consistent with household-finance evidence that literacy supports stock-market participation, diversification and better portfolio dynamics (van Rooij et al., 2011; Abreu and Mendes, 2010; von Gaudecker, 2015; Bianchi, 2018). In this framework, digital adoption creates access, while literacy increases the ability to translate access into a broader market-participation environment. This helps reconcile digital inclusion with financial capability: connectivity and account ownership can grow rapidly, but the welfare and portfolio consequences depend on what customers understand and do after access is obtained.

Finally, the cluster results refine rather than strengthen the moderation claim. A coefficient-only interpretation would label the mature-market effect 'stronger' because 0.563 exceeds 0.048. Yet the mature estimate is not statistically significant ($p=0.207$), whereas the low-access effect is significant. The defensible conclusion is therefore that the full-panel moderation is robust, while cluster-specific heterogeneity remains unresolved. This distinction illustrates why bank-marketing segmentation should combine effect size with uncertainty instead of converting descriptive market typologies into causal regimes.

5.2 Business implications for banks, digital platforms and investment-service providers

For banks and digital financial-service providers, the results argue against treating app adoption as the final marketing KPI. Account activation, monthly active users and transaction volume are useful, but they do not reveal whether digital relationships broaden customers' financial participation. Providers should therefore pair acquisition metrics with post-adoption indicators such as savings regularity, use of diversified investment products, portfolio concentration, risk-appropriate product holding and engagement with educational content. The positive adoption–diversification association means that post-adoption product architecture deserves the same strategic attention as onboarding.

The positive economic and social coefficients also suggest different levers from a technology-only strategy. In lower-capacity markets, product affordability, minimum balance/investment thresholds, transparent fees and simple small-ticket investment options may unlock economic value more effectively than adding sophisticated features. Social diffusion can be supported through trusted referral systems, peer learning, community ambassadors and credible communication, while maintaining safeguards against unsuitable product promotion. This is consistent with evidence that communication channels shape mobile-banking adoption and that social influence is important in technology acceptance (Tran and Corner, 2016; Venkatesh et al., 2012).

The negative functional coefficient should not be read as a reason to reduce digital infrastructure. Instead, it warns managers that infrastructure is often a hygiene factor. Once basic connectivity and app functionality are available, marginal feature expansion may not create proportional adoption because customers face different constraints—income capacity, trust, social learning or financial knowledge. Banks should therefore test whether new functions solve a salient customer job rather than assuming that more functions equal more value. Task–technology fit is particularly relevant here (Zhou et al., 2010).

The literacy interaction has a direct marketing implication: education should be embedded into the customer journey, not separated into corporate-social-responsibility activity. Contextual explanations of risk, scenario-based portfolio tools, plain-language fee disclosures, diversification prompts and access to appropriate human advice can increase the chance that digitally acquired customers use products competently. Yet education must be evaluated behaviourally because financial education does not always translate automatically into downstream action (Fernandes et

al., 2014; Kaiser and Menkhoff, 2017). Providers should therefore A/B test learning interventions against actual product use, concentration and retention outcomes while avoiding nudges that encourage excessive risk taking.

5.3 Government and regulatory advice

For government and financial regulators, the central implication is sequencing. Digital-inclusion policy should combine three layers: affordable access, capability and market integrity. Infrastructure and account access create an entry point; financial capability helps customers use that access; consumer protection and market supervision prevent broader participation from becoming broader exposure to unsuitable products, fraud or excessive speculation. The mobile-money literature shows that digital finance can produce material welfare benefits (Jack and Suri, 2014; Suri and Jack, 2016), but those benefits emerge within supporting institutional and user-capability conditions.

The findings also caution against measuring digital-finance success only by account ownership. Public dashboards should distinguish access, active use, investment participation, diversification, complaints, fraud losses and customer vulnerability. Such outcome-based monitoring would align regulatory objectives with the paper's finding that adoption has value when it is converted into healthier market participation. Financial-literacy initiatives should be evaluated with behavioural endpoints and targeted to moments when customers face real decisions, consistent with evidence that the effectiveness of financial education is context-dependent (Hastings et al., 2013; Kaiser and Menkhoff, 2017).

Finally, regulators should avoid assuming a single policy recipe across market clusters. The cluster analysis demonstrates substantial structural differences, but it does not prove that the moderation effect is stronger in mature economies. Policy segmentation should therefore be grounded in observed market constraints rather than the statistical significance of an exploratory cluster label. Low-access markets may prioritise affordable connectivity, identity/account access, basic investment literacy and fraud protection; mature markets may place more emphasis on product complexity, suitability, portfolio concentration, disclosure quality and the governance of digital advice.

5.4 Limitations and future research

The first limitation is measurement. The four value dimensions are national enabling-condition proxies rather than consumer perceptions. DIA uses account-ownership measures as an adoption proxy, FL is a capacity proxy rather than a direct financial-literacy test, and DIV captures equity-market breadth and activity rather than household portfolio holdings. The macro design is useful for comparison, but it cannot support an ecological inference about individual customers. Future studies should triangulate the panel with country-level direct literacy measures and household or brokerage portfolio data.

Second, several composites overlap empirically and conceptually. Private credit enters more than one construct, and internet reach contributes to multiple digital-capacity blocks. This is visible in the high pooled correlations, including ECON–EMO=0.98 and ECON–FL=0.91. Future work should test non-overlapping proxy sets, residualised or orthogonal components, alternative weighting schemes and leave-one-indicator-out sensitivity analyses. These checks are especially important before interpreting the negative functional and emotional coefficients as substantive within-country effects.

Third, the panel has only five waves. Driscoll–Kraay inference is attractive under cross-sectional dependence, but its asymptotic justification relies on the time dimension. Future robustness analysis should compare country-clustered, two-way clustered and appropriate small-sample or bootstrap inference when the underlying data and replication scripts are available. Dynamic specifications may also be considered because adoption is highly persistent.

Fourth, the cluster analysis is exploratory. The mature-market interaction is large but imprecise, and no formal test of the difference between cluster coefficients is reported. Future work should use interacted pooled specifications or formal slope-difference tests rather than comparing p-values across subgroups. The cluster map displays 75 countries while the panel contains 82; geospatial outputs should therefore document mapping coverage explicitly.

Finally, the diversification outcome is equity-centric. Digital financial relationships increasingly include bonds, funds, retirement products, cryptoassets and alternative investments. A broader multi-asset outcome could determine whether digital adoption encourages genuine diversification or merely increases trading intensity. Bank-level research could also connect platform design and educational interventions to risk-adjusted customer portfolio outcomes, which

would bring the macro findings back to the individual marketing mechanisms from which the theory originated.

6. Conclusion

This study re-examines the perceived-value logic of digital financial adoption at a cross-country level and links adoption to a post-adoption market outcome. Economic and social value-enabling conditions positively predict within-country adoption, while functional and emotional proxies reverse sign once country and year effects and the other value blocks are considered. The result is not a rejection of customer-level value theory; it is evidence that its macro translation has boundaries. Infrastructure and stability are not interchangeable with individual perceptions of functionality and reassurance.

More importantly for bank marketing, adoption is positively associated with the portfolio-diversification environment, and financial-literacy capacity strengthens that association in the full panel. Digital access therefore appears most consequential when customers and markets possess the capability to convert access into broader participation. For managers, this shifts attention from acquisition alone toward post-adoption capability and product use. For regulators, it supports a policy mix combining access, financial education, consumer protection and outcome-based monitoring. The paper thus advances a simple proposition with a demanding qualification: digital finance can widen participation, but value creation after adoption depends on the economic, social and knowledge conditions surrounding the customer.

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