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Toward an Integrated Entrepreneurial Ambidexterity Capability (IEAC) Instrument: A Pre-Content-Validation Pilot among Digitally Active Women Owner-Managers

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ABSTRACT

Purpose – This study proposes a construct framework and an initial, not yet content-validated item pool for Integrated Entrepreneurial Ambidexterity Capability (IEAC), the capability of women owner-managers of micro and small enterprises to refine and to renew digital practices when ambidexterity resides in the owner rather than in separate units.

Design/methodology/approach – The item pool, reviewed by the research team but not yet by independent experts or owner panels, was administered in Indonesia to 100 digitally active women owner-managers (96% in micro enterprises) recruited through a paid online panel. Exploratory factor analysis on Pearson and polychoric correlations was combined with four retention criteria and a response quality protocol separating established from author-developed diagnostics.

Findings/Results – The analyses are an analytical rehearsal on a provisional pool. Retention methods supported one to five factors; a five-factor solution matched the proposed sides only descriptively, and the four-factor solution merged the two finance sides. Item means were more uniform than an ordinal sensitivity analysis allows, and profile answers were internally inconsistent, so the responses cannot be assumed to follow item content. IEAC was also nearly unrelated to digital strategic orientation (r = 0.10). Several rival structures therefore remain plausible, and the higher order is untested.

Originality/Value – The paper contributes a candidate construct architecture, with improvisation kept outside the score and a higher order whose reflective or composite form is left open, and a methodological lesson: content validation and response-quality verification must precede any structural interpretation. It also registers the content-validation steps, verified-sample protocol, and falsifiable nomological test required next.

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1. Introduction

Firms that only refine existing routines become efficient but obsolete; firms that only experiment pay for search without reaping its returns. March (1991) framed this as a permanent resource-allocation problem between exploitation and exploration, and later work treats pursuing both as a higher-order dynamic capability (O'Reilly & Tushman, 2013; Teece, 2007). Large firms, the source of most evidence, typically place each mode in separate units; a meta-analysis of 114 studies shows such separation helps, contingent on environment and industry (Fourné et al., 2019). Micro and small enterprises lack this option: one owner performs both with the same time and money. Small-firm ambidexterity thus has heterogeneous drivers (Chakma & Dhir, 2024) and contested returns: Iborra et al. (2022) report an inverted U-shaped relationship between ambidexterity consistency and resilience, while Mendes et al. (2026) find focused strategies outperforming it in some environments.

The tension is acute in Indonesia, where more than 64 million MSMEs generate over 60 percent of GDP and almost 97 percent of employment but only about 15.7 percent of exports (Kementerian Koordinator Bidang Perekonomian, 2025). Women run about 64.5 percent of MSMEs, a share that declines as firms grow (Kementerian Komunikasi dan Digital, 2026). Digital adoption is associated with sales growth (Affandi et al., 2024), yet adoption is not capability. Women-owned enterprises show a gap between acquired skills and business results (Pranitasari, Harini, et al., 2026), and high digital awareness coexists with limited use owing to skill, time, licensing, and asset-ownership constraints (Pranitasari, Suriawinata, et al., 2026). The decisive question is therefore not whether an owner uses a digital channel, but whether she can refine current use while experimenting with new ones.

Answering it is hindered because marketing and finance, small firms' most critical domains, are studied separately. Digital marketing capability is an established performance-relevant dynamic capability (Elkhoudary et al., 2026; Hazzam et al., 2025), including among Indonesian SMEs (Hidayati et al., 2025); Liu et al. (2026) modelled it as higher-order, but along marketing functions rather than learning modes. Finance research emphasizes literacy and inclusion rather than capability (Al-shami et al., 2024; Hasan et al., 2023; Tandilino et al., 2025), Indonesian studies of women-owned firms treat literacy and fintech adoption as levels of knowledge or use (Kurniasari & Lestari, 2024; Pranitasari, Harini, et al., 2026), and Sumail et al. (2026) measured financial ambidexterity without linking it to marketing. Three measurement problems result. First, existing scales presuppose separate units and describe practices owners do not recognize. Second, no instrument captures marketing and financial ambidexterity within one framework, although both compete for the same owner's attention. Third, small-firm studies form difference or product scores without showing that the sides are distinct, although difference-score reliability drops sharply when components correlate highly (Edwards, 2001; Rosing & Zacher, 2017).

This study therefore defines Integrated Entrepreneurial Ambidexterity Capability (IEAC) as a higher-order dynamic capability formed by the exploitation and exploration sides of digital marketing and digital financial capability. Improvisation capability is specified as an adjacent enabling mechanism: it is measured alongside IEAC but is not one of its components, nor a third side. "Integrated" is a theoretical claim, not pooled item lists: absent separate units,

ambidexterity arises from the owner running both modes within each domain, with improvisation enabling unplanned switching. Hence, items should cluster by side within domains, with improvisation items forming a distinct factor. The study aims to (a) operationalize IEAC in items reflecting owners' daily behavior, (b) document the content review completed so far and the independent content validation still required, (c) examine initial factor structure and internal consistency against a rival model specified in advance, and (d) specify the content-validation and verified-sample steps that must precede any use of the instrument.

The instrument is meant to reveal what existing measures cannot. Adoption and usage indices record whether an owner has a channel or an account (Affandi et al., 2024), so two owners with identical adoption profiles look the same even when one only repeats a routine and the other refines it while also testing new practices. Literacy and competence scales record what an owner knows or can deploy (Hasan et al., 2023; Yu & Moon, 2021), not how she divides scarce effort between refining and searching. Existing ambidexterity scales presuppose separate units, describe individual work behavior in general terms (Rosing & Zacher, 2017), or cover one domain (Sumail et al., 2026). None of them can show whether an owner who explores in marketing also explores in finance, or whether search in one domain is paid for by neglect of routines in the other. IEAC targets this within-owner, cross-domain profile; Table 1 sets out the boundaries. The scope of the empirical part must also be stated at the outset. It is a pre-content-validation pilot: the item pool has not yet been rated by independent experts, the respondents are digitally active women owner-managers of mostly micro enterprises, and the data showed response-quality problems. The analyses demonstrate the procedure and identify which decisions content validation and a verified sample must settle. They neither establish the instrument nor adjudicate its dimensionality. The evidence is ordered accordingly: content validity comes first and structural validity second. Until independent experts and owner-managers establish definitional correspondence and content coverage, the factor analyses are an analytical rehearsal on a provisional item pool, not preliminary confirmation of the construct architecture.

2. Literature Review & Hypothesis Development

2.1 Dynamic Capability Theory

Teece et al. (1997) defined dynamic capability as a firm's ability to combine, build, and reorganize its internal and external skills to deal with a fast-changing environment. Teece (2007) later divided it into three microfoundations: sensing opportunities, seizing opportunities, and transforming assets. Eisenhardt and Martin (2000) added a different emphasis. They argued that dynamic capabilities are specific routines that can be identified in practice, not abstract ideas floating above practice.

We chose this framework, rather than the resource-based view alone, because of our research question. The resource-based view explains why firms differ from one another. Dynamic capability theory explains how these differences are renewed when the environment changes. Our construct is the ability to renew, not the ownership of resources, so dynamic capability theory is the right fit. Teece (2014) clearly describes ambidexterity as a detailed form of

dynamic capability. This statement links the grand theory to the middle-range theory used in this study.

2.2 Organizational Ambidexterity

March (1991) distinguished two learning modes: exploitation (refinement, selection, efficiency, execution) and exploration (search, variation, risk-taking, experimentation), which compete for scarce resources, so that overemphasizing either leads to competence traps or unrewarded experimentation. He and Wong (2004) first showed that the interaction of the two strategies is positively, and their imbalance negatively, related to sales growth. Raisch et al. (2009) identified unresolved tensions in this literature, including whether ambidexterity arises through separation or integration and at which level; Andriopoulos and Lewis (2009) showed that these tensions operate simultaneously across strategic intent, customer orientation, and personal drivers; and O'Reilly and Tushman (2013) concluded that ambidexterity is best understood as a dynamic capability of top management. Of the structural, contextual, and sequential routes to ambidexterity, none fits enterprises with fewer than twenty workers: there are no units to separate, no middle managers to balance demands, and planning horizons too short for temporal switching. In Indonesian creative-based SMEs, ambidexterity accordingly depends on the creative leadership of the leader (Restuputri et al., 2024). Ambidexterity in this segment must therefore be defined at the level of the owner-manager's behavior within specific business domains, answering the call of Wilden et al. (2018) for microfoundational research.

2.3 Defining the IEAC Construct

Defined before operationalization (Clark & Watson, 2019; Lambert & Newman, 2023), IEAC is the micro- or small-enterprise owner-manager's higher-order dynamic capability to simultaneously improve current and try new digital practices in marketing and finance, with improvisation enabling unplanned switching. It differs from adoption (use versus management), literacy (knowledge versus behavior), orientation (attitude versus action), and performance, which it may explain. Following March (1991), not Liu et al.'s (2026) functional structure, marketing exploitation refines promotions, listings, and proven content, while exploration tests new channels, buyers, and formats. Financial exploitation covers expense separation, digital bookkeeping, and cost review; exploration, untried services, payment methods, and funds for uncertain activities.

The elements relate to one another in a specified order. At the first order, IEAC comprises four side-by-domain capabilities: marketing exploitation, marketing exploration, financial exploitation, and financial exploration. The higher-order construct is the owner's capacity to sustain both sides in both domains; how it relates to the four capabilities is specified below. Improvisation stays outside this structure. It is a domain-free way of acting that makes unplanned switching between sides possible, so theory places it as an enabler of IEAC and it is excluded from any IEAC score.

How the four capabilities form the higher order is a separate question, and theory alone does not settle it. Jarvis et al. (2003) proposed four criteria: the direction of causality, the interchangeability of indicators, whether the indicators are expected to covary, and whether they share antecedents and consequences. Two criteria point toward a formative or composite

higher order. An owner strong in three sides but weak in financial exploration differs in substance from one strong in all four, so the sides are not interchangeable, and omitting one changes what the construct means. The other two point toward a reflective higher order. All four sides draw on the same owner's time, attention, and cash, which supplies a plausible common cause and leads one to expect covariation. IEAC is therefore specified with its higher order left open. A reflective second-order model (M5 in Table 12) tests whether the sides share a common factor. A reflective-formative model (M7), in which the reflective first-order sides combine into a weighted composite (Schuberth et al., 2018), represents IEAC as a non-interchangeable profile. Support for M5 would show statistical commonality among the sides. It would not show that a reflective higher order is conceptually correct.

Three properties make the combination a capability rather than a collection of related business practices. First, the four sides draw on one owner's time, attention, and cash, so they are interdependent: an afternoon spent courting new buyers is an afternoon not spent on the books. Second, the capability lies in holding exploitation and exploration together within each domain, which is March's (1991) tension relocated from the organization to the owner. Third, the domains are coupled. Marketing experiments create transactions that financial routines must absorb, and a new payment or cash-management tool changes which marketing experiments the owner can afford. A list of practices predicts none of these dependencies. A capability predicts correlated but distinct sides together with either a shared higher-order factor or a stable composite profile, which is what the later tests examine.

IEAC does not assume that both domains follow the same exploitation–exploration structure. In marketing, exploration can run beside existing routines, because a new platform can be tried while proven listings continue. In finance, most exploratory moves in a micro enterprise, such as adopting a new payment feature or a digital cash-management service, are built on the very recording and payment routines that make up exploitation, so the two sides should correlate more strongly. Small-firm evidence leaves room for such asymmetry: exploration and exploitation carry different consequences for international SMEs (Su et al., 2022), and financial ambidexterity has been modelled as a construct of its own (Sumail et al., 2026). IEAC is therefore defined by the presence of both sides in both domains, not by an equal degree of separation, and the degree of separation in each domain is treated as an empirical question (P1 and P4).

Table 1. Boundaries between IEAC and adjacent constructs

Construct (example source)	What it captures	What it cannot reveal that IEAC is designed to reveal
Digital adoption and usage (Affandi et al., 2024)	Whether, and how often, the owner uses digital channels or accounts	Whether use is refined over time or extended to untried practices; adoption measures reach a ceiling once use is universal
Digital and digital financial literacy (Al-shami et al., 2024; Hasan et al., 2023)	Knowledge of digital tools and financial concepts	Whether knowledge becomes behavior, and how effort is split between refinement and search

Construct (example source)	What it captures	What it cannot reveal that IEAC is designed to reveal
Digital competence (Yu & Moon, 2021)	An enterprise's ability to deploy digital technology	Behavior of the owner within specific domains; the exploitation–exploration tension
Digital marketing capability (Hazzam et al., 2025; Liu et al., 2026)	Marketing functions carried out through digital means	The learning mode (refining versus searching) and the link to financial routines
Financial ambidexterity (Sumail et al., 2026)	Exploitation and exploration in financial management	Coupling with marketing, which competes for the same owner's attention and cash
Individual ambidexterity (Rosing & Zacher, 2017)	General exploration and exploitation behavior of individuals at work	Domain specificity in an enterprise run without separate units
Digital strategic orientation (Yu & Moon, 2021)	Strategic attitude toward customers, competitors, and technology	Whether attitude has turned into daily practice
IEAC (this study)	Owner-level exploitation and exploration in digital marketing and digital finance, organized as a higher-order capability	Improvisation (Ciuchta et al., 2021) is measured alongside as an enabling mechanism and is not part of the IEAC score

Note. *Sources are examples of each measurement tradition, not an exhaustive list.*

Financial exploration is anchored in money management, not fund-raising, because credit access reflects eligibility and structural barriers, including asset ownership and licensing (Pranitasari, Harini, et al., 2026; Pranitasari, Suriawinata, et al., 2026), not capability. Improvisation, comprising concurrent planning and execution, spontaneity, and resourcefulness (Ciuchta et al., 2021), drives innovation (Chen et al., 2023), including digital innovation under resource constraints (Tariq et al., 2026), with effects differing by dimension (Hultman et al., 2022). As an enabling mechanism, not a third side, its items describe how rather than where owners act, avoiding circularity with ambidexterity scores.

2.4 Digital Strategic Orientation as a Companion Construct

Digital strategic orientation was measured in the same pilot study because it is specified as an antecedent of IEAC in the subsequent structural model, so its measurement structure, and its empirical separation from IEAC, must first be established empirically. Following Yu and Moon (2021), who tested the construct with 160 Chinese enterprises, it comprises three dimensions, operationalized here as customer orientation, the use of digital means to understand and respond to customers; competitor orientation, the monitoring of competitors' digital moves; and technology orientation, the commitment to adopting and using digital technologies. Two departures from the original source must be acknowledged. First, Yu and Moon (2021) modelled the three orientations as separate predictors rather than as a higher-order construct, and competitor orientation was not significant in their model; this study instead specifies digital strategic orientation as a reflective-formative higher-order construct. Second, this specification can be examined only partially here, because exploratory factor analysis tests the reflective first-order structure but not the formative combination at the

second order, which requires a separate two-stage procedure in future research. Accordingly, the pilot evaluates whether the items form three distinct, moderately correlated factors (P3) and whether these factors are empirically separable from the IEAC dimensions.

2.5 Propositions about the Factor Structure

Because this study is exploratory, we state propositions about the factor structure, not hypotheses about relationships between constructs.

P1. Digital marketing and digital financial items separate by side within each area, producing four correlated first-order factors.

P2. Improvisation items form one single factor that is separate from these four factors.

P3. Digital strategic orientation items form three moderately correlated first-order factors that match the customer, competitor, and technology dimensions.

P4. As a rival model registered in advance, digital marketing and digital financial items group by area rather than by side, producing two factors.

We registered rival model P4 in advance on purpose. An earlier test with a smaller sample suggested a structure by area, so we treated both possibilities as open and prepared arguments for both. This step follows the advice of Lambert and Newman (2023), so that the judgment of construct validity does not depend on explanations made after seeing the results.

Two clarifications follow from the construct definition. P1 states the strongest version of the theory, with symmetric separation in both domains. A mixed outcome, with separate sides in marketing and merged sides in finance, would not falsify IEAC; it would indicate that the financial sides need a different scoring rule. The propositions also concern the first-order structure only. Whether a higher-order IEAC factor is defensible, and therefore whether a single overall IEAC score may be reported, is not tested here. That question is left to the confirmatory comparison of the rival structures listed in Table 12, including the reflective and composite higher-order specifications discussed above.

3. Methodology

3.1 Research Design

This study uses the three-phase scale development design described by Boateng et al. (2018): item development and content validity, scale construction, and scale evaluation. The first phase is reported only in part. The content review by the authors and the cognitive interviews are complete, but the independent expert rating and owner sorting that the phase requires are not; they are specified below. The empirical work is therefore a pre-content-validation pilot of an initial item pool. From the third phase, we report a first look at dimensionality and internal consistency on this pool, as a demonstration of the procedure rather than a test of the construct's dimensionality. Confirmation of the structure with confirmatory factor analysis on a verified sample and full testing of nomological validity are stated from the start as future work, not hidden as limitations at the end of the paper. Because content validity is logically prior to structural validity (Boateng et al., 2018; Colquitt et al., 2019), the structural analyses can describe only the provisional pool until that step is complete.

3.2 Item Development and Content Review

IEAC items were generated from each domain's literature (Appendix A); 19 were retained after content review (six marketing, six finance, seven improvisation), plus 15 adapted digital strategic orientation items (Yu & Moon, 2021) and four anchor/global items. Each item uses a distinct verb and concrete behavior rather than a shared stem with a swapped object. Parallel wording, such as "use digital data to find new opportunities" versus "use digital data to improve what already works," would inflate the cross-side correlation, the quantity examined; Clark and Watson (2019) likewise prioritize unidimensionality over mere internal consistency. The content rules behind the item pool are now stated explicitly, so that they can be checked by others. An item belongs to IEAC only if it describes (a) a behavior the owner performs herself, (b) through a digital means, (c) that falls on one side within one domain, and (d) whose frequency depends on the owner's choices rather than on access. Rule (d) addresses the main threat to content validity in this population. A marketplace or bank may make a feature available to everyone, so frequent use can reflect provision rather than capability. Exploration items are therefore written around a first or trial use with an uncertain result, such as testing a promotion format not used before, whereas exploitation items describe revising a practice already in place in light of its results. Statements of account ownership, platform membership, or familiarity with a tool are adoption indicators under these rules and do not enter the IEAC pool. Table 2 maps the facets of each dimension against the current version and lists facets that are not yet covered, which is where overlooked behaviors are most likely to sit.

Table 2. Content coverage of the IEAC dimensions

Dimension	Facets addressed by the current items	Facets not yet covered (candidates for the next version)
DMC exploitation	Refining promotions to existing buyers; improving product listings; reusing content that has worked	Using platform or sales analytics to adjust prices or stock; responding to reviews or complaints to improve existing listings
DMC exploration	Testing new channels; reaching new buyer groups; trying new content or promotion formats	Trying live selling or affiliate arrangements; small, capped trials of paid digital advertising
DFC exploitation	Separating business from household expenses; digital bookkeeping; reviewing costs	Reconciling marketplace and e-wallet settlements; keeping digital records needed for tax or levies
DFC exploration	Trying untried financial services and payment methods; setting aside funds for uncertain activities	Trying digital cash-management or savings tools; first use of digital invoicing or supplier payment
Improvisation capability	Concurrent planning and execution; spontaneity; resourcefulness (Ciuchta et al., 2021)	Enough items per sub-dimension to test dimension-specific effects (Hultman et al., 2022)

Note. *Credit and fund-raising behaviors are excluded by design. Candidate facets will be submitted to the expert and owner panels described below before any are added.*

Content was reviewed in several rounds by the first author and two senior small-business researchers (the second and third authors), judging fit to dimension definitions, clarity for owners, and distinctness across domains. Because quantitative ratings require at

least three independent raters (Lynn, 1986), no content validity index was computed. Independent rating is therefore the main gap in the content evidence, and the present review cannot show that the items cover the full meaning of each dimension. Cognitive interviews with owners resembling the target population checked that items were understood as intended, with Appendix C summarizing the content review and the wording changes that resulted. Marketing and finance items, describing countable behaviors, used a five-point past-year frequency scale (never to always); improvisation and digital strategic orientation items, capturing tendencies, used a five-point agreement scale.

This gap limits the empirical part directly. Factor analysis can only sort the items that were written. It cannot recover facets that are absent from the pool, such as the analytics-based price and stock adjustment, responses to reviews, live selling, settlement reconciliation, digital invoicing, and digital cash-management tools listed in Table 2. The factor results reported below therefore describe the current pool; they cannot adjudicate the dimensionality of IEAC as defined above. A clean solution on this pool would show how the written items group, not that the dimensions of IEAC have been recovered, so the factor analyses are reported as a rehearsal of the procedure rather than as preliminary evidence of the construct architecture.

Independent content validation is therefore an essential stage of construct development, not an improvement deferred to a later version, and it will be completed in two steps before any new data are factor-analyzed. First, a panel of at least six independent experts, none of them authors, drawn from entrepreneurship, digital finance, measurement, and research on women-owned enterprises, will rate each item's relevance to its dimension definition on a four-point scale. Item-level and scale-level content validity indices will be reported with the computation method stated (Lynn, 1986; Polit & Beck, 2006). The panel will also judge definitional distinctiveness, that is, whether each item corresponds more closely to its own definition than to the definitions of the other sides, of digital adoption, and of digital literacy (Colquitt et al., 2019). Second, owner-managers stratified by digital experience (low, moderate, and high) will sort the items into dimension definitions and take part in cognitive interviews. These interviews will check in particular whether owners with little digital experience read exploration items as questions about access rather than about trying something new. Items that fail either step will be revised or replaced from the candidate facets in Table 2.

3.3 Population, Sample, and Screening

The target population of the pilot is digitally active women owner-managers of micro and small enterprises in Bandung, Bogor, Denpasar, Depok, Greater Tangerang, Jakarta, Makassar, Medan, Semarang, Solo, Surabaya, and other cities in Indonesia, that is, owners who already use digital channels for both marketing and finance. The sampling technique was non-probability sampling, specifically judgmental (purposive) sampling.

A woman owner-manager is defined here as a woman who holds an ownership stake in the enterprise and is its principal day-to-day decision maker. The definition separates management from ownership. It does not require majority ownership, so the pilot does not measure women-owned enterprises in the majority-ownership sense, and the paper therefore uses the term owner-manager. Majority ownership may matter for IEAC: control over assets, financing, and strategic decisions can differ between majority owners and minority owner-

managers, and these are the conditions that shape digital financial ambidexterity. The verified sample will record ownership share and authority over financial decisions and report results separately for majority (more than 50 percent) and minority owners. Enterprise size follows Government Regulation No. 7 of 2021. A micro enterprise has annual sales of up to IDR 2 billion, or business capital of up to IDR 1 billion excluding land and buildings; a small enterprise has annual sales above IDR 2 billion and up to IDR 15 billion, or capital above IDR 1 billion and up to IDR 5 billion (Pemerintah Republik Indonesia, 2021). The pilot could classify size by revenue only.

The screening criteria and the reasons for them are shown in Table 3. Three criteria were used to exclude respondents. The other three were specified as profile variables to be recorded.

Table 3. Respondent screening criteria

Criterion	Treatment	Reason
Woman owner-manager	Exclude	The construct and instrument are designed for this population
Uses digital channels for marketing	Exclude	Respondents who do not use them would give the same answer to all marketing items, and constant items damage the correlation matrix
Uses digital channels for finance	Exclude	Same reason, for the finance area
Number of workers	Record only (specified; absent from the analyzed dataset)	Treated as a boundary condition to be tested, not as a screen
Business age	Record only (specified; absent from the analyzed dataset)	Digital behavior does not require a certain business age
Ownership share	Record only (specified; absent from the analyzed dataset)	A minority owner who runs the business can still report its behavior; the verified sample will record ownership and report majority and minority owners separately

We deliberately chose not to exclude respondents based on the number of workers. A rule that excludes businesses with no workers other than the owner would remove most women-led businesses, because solo businesses are the most common form in this segment. The number of workers was specified as a profile variable, but it is absent from the dataset available for analysis, so size can only be approximated by revenue in the pilot. It will be tested as a boundary condition in future research, especially to test the idea that only small firms can be ambidextrous while micro firms are in survival mode.

The two digital-use screens define the scope of the instrument in its current form. They are needed because owners without digital marketing or digital finance would answer every item in that area with the lowest category. The price is range restriction. The owners most likely to sit at the bottom of the capability continuum are excluded, so the instrument can rank owners who already use digital channels, but it cannot tell whether a low score reflects weak

capability, lack of access, non-adoption, or deliberate non-use. As measured here, IEAC is an instrument for digitally active owner-managers. Extending it to all women-led micro and small enterprises would require a routing, or hurdle, structure: an access and adoption module first, then the exploitation and exploration items for eligible users only, with non-users analyzed as a separate group rather than scored as low on IEAC.

We did not set the sample size using a simple cases-per-item rule. MacCallum et al. (1999) showed that such ratios are misleading when separated from two other conditions: the size of the communalities and the number of items per factor. When communalities are high and factors are well defined, a sample much smaller than the usual advice can still recover the true structure. When communalities are low and factors have only a few items, a sample of one hundred is not enough. Hogarty et al. (2005) and Mundfrom et al. (2005) reached similar conclusions. Because the four IEAC factors in this study have only three items each, this study falls in the condition that needs a large sample. The 100 responses obtained are therefore treated as a pilot sample for an initial check of the factor structure, not as a basis for final conclusions about the instrument, and the structure is to be confirmed on a larger independent sample.

3.4 Data Collection and Response Quality Protocol

Data were collected online in June–July 2026. Because paid online panels are vulnerable to careless and fraudulent responding (Chandler et al., 2020; Ward & Meade, 2023), yet Indonesian MSE studies using them rarely report quality checks, all responses were screened. The checks are of two kinds and are reported separately. Two are established case-level diagnostics (Curran, 2016; Meade & Craig, 2012): straight-lining, screened through within-person standard deviations and identical-answer run lengths, and identical or near-identical response patterns. The other two are sample-level diagnostics developed by the authors for this study, and they are not validated decision rules. Check 2 examined whether self-reported frequency of digital channel use tracked digital capability scores. Its premise is weaker than first assumed, because this paper argues that use is not capability; a weak correlation may partly reflect the distinction the instrument is meant to capture, so Check 2 is treated as a plausibility check only. Check 3 asked whether the item means were more homogeneous than sampling error allows when all items have equal true means. Equal true means is the null most favorable to homogeneity, since any real difference in item difficulty or prevalence would widen the spread of the means. Check 3 was run first with a multivariate normal model and then, as a sensitivity analysis, with five-category ordinal data and inflated inter-item correlations. Logically linked profile answers were also compared. Flagged cases were to be reviewed individually before exclusion, and the structure was to be read as an instrument property only if the data passed the protocol.

3.5 Data Analysis

Factorability used Kaiser-Meyer-Olkin (KMO ≥ 0.70; items ≥ 0.60) and Bartlett's test (Howard, 2016; Watkins, 2018). Principal axis factoring, which unlike principal components separates common from unique variance (Costello & Osborne, 2005; Goretzko et al., 2021), was paired with promax rotation, given correlated dimensions (Worthington & Whittaker, 2006). Retention combined parallel analysis of full (Horn, 1965) and reduced (Crawford et al., 2010)

matrices, Velicer's (1976) minimum average partial (MAP) test, and the empirical Kaiser criterion (EKC; Braeken & van Assen, 2017), comparing solutions when criteria disagreed (Lim & Jahng, 2019).

Items required loadings ≥ 0.40, cross-loadings < 0.32, gaps ≥ 0.20 (Howard, 2016; Worthington & Whittaker, 2006), and communalities ≥ 0.40 (Hogarty et al., 2005); internal consistency was described provisionally with standardized α (≥ 0.70) and corrected item-total correlations (≥ 0.30). Composite reliability and average variance extracted were computed from one-factor solutions per subscale for completeness; because they presuppose a measurement model that only confirmatory analysis can establish (Cheung et al., 2024), they are not interpreted as evidence of convergent validity. Blocks were analyzed separately, then jointly, excluding anchor/global items. Because the items are five-point ordinal responses, the IEAC block was re-analyzed with polychoric correlations and with parallel analysis based on polychoric eigenvalues (Garrido et al., 2013; Holgado-Tello et al., 2010) as a robustness check. Item correlations were first obtained in SPSS 27; all computations were then run in Python on the item-level data, and a script that reproduces every result is supplied (Appendix B). For brevity, "IEAC block" denotes all 19 instrument items, including the improvisation items that are measured alongside IEAC but are not part of its score.

3.6 Protocol for the Independent Validation Sample

Because the pilot data cannot carry substantive conclusions, the next stage collects a new sample under rules fixed before data collection. Recruitment will run through identifiable entrepreneur networks rather than a paid panel: women-entrepreneur associations, cooperatives, business-support organizations, and government or university MSME incubation programs whose membership records allow eligibility to be confirmed. Where participants consent, eligibility will be verified against an active online storefront or a business identification number (NIB). Ownership share, authority over financial decisions, number of workers, and business age will be recorded, so that enterprise size can be classified under Government Regulation No. 7 of 2021 with more than revenue alone. Verification details will be stored apart from questionnaire responses and deleted once checked, and the study will proceed only after ethics approval.

Careful completion will be supported in the questionnaire itself. Two instructed-response items and one bogus item will be embedded (Meade & Craig, 2012), completion time and other paradata will be recorded, and the profile items will include logically linked questions so that internal consistency can be checked case by case. The pilot's response quality checks will be applied with thresholds registered in advance. The established case-level checks, together with the instructed-response and bogus items, will determine exclusions. Check 3 will be applied with the ordinal null used in the pilot, and Check 2 will serve only as a plausibility comparison between owners with low and high reported digital use. Factor-analytic results will be interpreted only if, after the registered exclusions, the sample shows no warning on any of these checks.

Sampling will deliberately widen the pilot's profile, with quotas for micro and small enterprises (at least 150 small enterprises), urban and non-urban locations, education levels, and digital experience, so that invariance across these groups can be tested. Given three-item

factors and the disagreement among retention methods, the target is at least 500 verified responses (Auerswald & Moshagen, 2019), randomly split into a calibration half for exploratory analysis and a holdout half for confirmatory comparison of the rival structures in Table 12. Both halves will be analyzed with methods for ordinal data: polychoric correlations and ordinal parallel analysis in the calibration half, and an estimator for categorical indicators in the holdout half.

The relationship between IEAC and digital strategic orientation will be registered as a falsifiable prediction, not examined as an exploratory correlation. Theory and prior evidence predict a positive relation (Khin & Ho, 2019; Yu & Moon, 2021; Zhang et al., 2025). The registered prediction is a latent correlation of at least 0.30 between digital strategic orientation and each of the four side factors in the holdout half, and the prediction is rejected for a side if the upper limit of its 95% confidence interval falls below 0.20. Orientation will be measured about two weeks before the capability items, a temporal separation that Podsakoff et al. (2012) recommend against shared method variance, so that a positive result cannot be produced by common method alone. If the prediction fails for three or four sides on verified data, the construct definition or the measurement model will be reconsidered rather than the null explained after the fact; failure for one or two sides will lead to re-examination of those subscales. A positive result would count toward nomological validity only together with the content and structural evidence, following the logic of a nomological network (Cronbach & Meehl, 1955).

4. Results and Discussion

4.1 Respondent Characteristics

Table 4. Respondent characteristics (n = 100)

Characteristic	Category	f	%
Age	20-29 years	14	14
	30-39 years	37	37
	40-49 years	27	27
	50-59 years	14	14
	60 years and above	8	8
Education	Senior high school	34	34
	Diploma	9	9
	Bachelor	38	38
	Master	15	15
	Doctorate	4	4
Marital status	Married	69	69
	Never married	20	20
	Divorced	8	8
	Widowed	3	3
Lives with	Husband/partner	29	29
	Children	34	34
	Parents/parents-in-law	16	16
	Alone	15	15

Characteristic	Category	f	%
	Other	6	6
School-age children	None	35	35
	Preschool/kindergarten	19	19
	Primary school	18	18
	Junior/senior high school	19	19
	No answer	9	9
Family involvement in the business	None	26	26
	Occasionally	48	48
	Every day	26	26
Monthly revenue (IDR)	< 30 million	47	47
	30-50 million	26	26
	> 50-100 million	11	11
	101-167 million	12	12
	> 167 million	4	4
Business sector	Food and beverage	21	21
	Fashion	20	20
	Handicrafts	17	17
	Services	13	13
	Retail (small shop)	12	12
	Beauty	8	8
	Manufacturing	5	5
	Livestock/fisheries	2	2
	Agriculture/plantation	2	2
City of residence	Jakarta	19	19
	Greater Tangerang	13	13
	Bogor	11	11
	Depok	5	5
	Bandung	17	17
	Surabaya	13	13
	Semarang	5	5
	Solo	4	4
	Denpasar	3	3
	Makassar	3	3
	Medan	2	2
	Other	5	5
Frequency of digital channel use	Very often	33	33
	Often	41	41
	Sometimes	18	18
	Rarely	6	6
	Very rarely	2	2

Note. n = 100, so frequencies equal percentages. Revenue is in million rupiah per month.

Table 4 shows the respondent profile. Three features of the sample limit how far the findings can be generalized. First, respondents came from eleven named cities, with 5 percent from other cities. Almost half (48 percent) lived in Greater Jakarta, and most of the rest lived in Bandung (17 percent) and Surabaya (13 percent). The findings therefore mainly represent urban business owners in Java. Second, the respondents were highly educated: 57 percent held a bachelor's degree or higher, including 19 percent with a postgraduate degree. Third, based on revenue, almost all respondents ran micro enterprises. As many as 96 percent reported a monthly revenue of no more than IDR 167 million, or about IDR 2 billion per year, and only 4 percent fell in the small enterprise category. In addition, eight respondents said they used digital channels rarely or very rarely, even though they had passed the screening for digital channel use. Table 3 lists the number of workers, business age, and ownership share as profile variables, but none of the three is present in the dataset available for analysis. Size could therefore be classified by revenue alone, ownership could not be separated from management, and with only four small enterprises the pilot provides no basis for judging how the instrument behaves in small enterprises. The empirical evidence concerns digitally active women owner-managers of predominantly urban micro enterprises.

4.2 Response Quality

Table 5. Results of the response quality protocol

Check	Criterion	Result	Outcome
1. Straight-lining (established)	Within-person SD near zero; long identical-answer runs	Within-person SD 0.69 to 1.24 across the 38 items (median 0.93); lowest block-level SD 0.51 (IEAC) and 0.46 (digital strategic orientation); longest identical run 9 of 38 items	No case flagged
2. Convergence with reported digital use (author-developed)	Clearly positive Spearman correlation between frequency of digital channel use and digital capability scores	$\rho = 0.03$ ($p = 0.75$) for DMC, 0.14 ($p = 0.16$) for DFC, and 0.11 ($p = 0.27$) for both domains combined; owners reporting rare digital use scored lower (mean 2.86 versus 3.17)	Failed as specified; treated as non-diagnostic
3. Marginal uniformity (author-developed)	Dispersion of item means not smaller than expected under equal true means	SD of item means 0.038 for IEAC (simulated median 0.083; 95% interval 0.054 to 0.122) and 0.041 for digital strategic orientation (0.083; 0.052 to 0.129); none of 5,000 simulated samples for all 34 items was as homogeneous as the observed data ($p < 0.001$). Ordinal sensitivity analysis: IEAC $p < 0.001$ (observed R), ≤ 0.003 (R + 0.10 or + 0.20); all 34 items $p < 0.001$	Failed; robust to the sensitivity analysis
4. Duplicates (established)	Identical or near-identical response patterns	No identical rows; highest agreement between any two respondents 53 percent of items (mean 26 percent)	No case flagged

Note. *n = 100. Simulations drew 5,000 samples of 100 cases from a multivariate normal distribution with the observed item covariance matrix and equal means. The ordinal sensitivity analysis drew 3,000 samples of five-*

category data from a latent normal model with the observed inter-item correlations (or correlations raised by 0.10 or 0.20) and thresholds pooled across items, so that all items shared one true distribution. Established checks follow Curran (2016) and Meade and Craig (2012); author-developed checks are not validated decision rules.

Table 5 reports the results of the response quality protocol. The two established case-level diagnostics flagged no respondent, so no case was excluded. The two author-developed, sample-level checks need more careful reading. Check 2 failed as originally specified: self-reported frequency of digital channel use was unrelated to the capability scores. Because frequent use need not imply capability, this result is not taken as evidence of poor quality. A weaker plausibility test was more reassuring. The eight owners who reported using digital channels rarely or very rarely had lower digital marketing and financial scores than the other respondents (mean 2.86 versus 3.17; 29 versus 39 percent of their answers in the often or always categories).

Check 3 failed and survived the sensitivity analysis. The 34 item means ranged only from 3.06 to 3.23, so items describing very different behaviors, such as sending offers to past buyers and testing a new promotion format, had practically identical means. When the null was rebuilt with five-category ordinal data, using thresholds pooled across items so that every item shared the same true distribution, the dispersion of the IEAC item means (0.038) still fell below every simulated value (simulated median 0.085; 95% interval 0.056 to 0.121). Raising every inter-item correlation by 0.10 or 0.20, which makes the null more homogeneous, left the conclusion unchanged for IEAC ($p \leq 0.003$) and for all 34 items ($p < 0.001$); for the digital strategic orientation block alone, p rose to 0.017. Check 3 is still an author-developed diagnostic without an external validation study. It is therefore reported as a warning signal rather than as a decision rule that invalidates the sample on its own.

Two further patterns, which do not depend on the author-developed checks, point in the same direction. First, the profile variables were inconsistent with one another. Five of the 14 respondents aged 20 to 29 reported children of junior or senior high school age, four of the eight respondents aged 60 or older reported children in preschool or primary school, and age was unrelated to the age of children (χ^2, $p = 0.90$). Eight of the 20 never-married and four of the eight divorced respondents reported living with a husband or partner, whereas only 17 of the 69 married respondents did. Second, none of the composite scores differed by revenue, education, age, sector, or city (Kruskal-Wallis tests, all $p \geq 0.17$). Taken together, these results indicate that the responses cannot be assumed to reflect owners' answers to item content. The analyses that follow are therefore reported in full for transparency and as a demonstration of the analytic procedure, not as evidence about the instrument. Each result that follows describes how the procedure behaves on these data. It would have to be reproduced on a verified sample before it could be attributed to the instrument. From here on, every result carries two qualifications: it concerns a provisional pool that has not been content-validated, and data whose responses cannot be assumed to follow item content. The factor analyses that follow are therefore an analytical rehearsal of the procedure, not preliminary confirmation of the construct architecture.

4.3 Suitability of the Correlation Matrix

For the IEAC block, the overall KMO was 0.875. Item values ranged from 0.705 to 0.940, with the lowest value for item DMC3. Bartlett's test gave a chi-square of 833.95 with 171 degrees of

freedom ($p < 0.001$). For the digital strategic orientation block, the overall KMO was 0.859, with item values from 0.794 to 0.896. Bartlett's test gave a chi-square of 562.27 with 105 degrees of freedom ($p < 0.001$). Both matrices were suitable for factor analysis. In the combined analysis of 34 items, the overall KMO dropped to 0.778, and two items fell below the item threshold of 0.60: DMC3 (0.575) and CUST3 (0.594). This drop fits with the weak correlation between the two blocks, described below.

4.4 Deciding the Number of Factors

Table 6. Comparison of methods for deciding the number of factors, IEAC block

Factor	Eigenvalue, full matrix	Random 95th percentile, full matrix	Eigenvalue, reduced matrix	Random 95th percentile, reduced matrix	Methods that keep this factor
1	7.083	2.038	6.610	1.266	All methods
2	1.757	1.809	1.251	1.030	PA reduced, MAP r^2, EKC, K1, PA full (mean cut-off)
3	1.551	1.652	1.061	0.868	PA reduced, MAP r^2, EKC, K1
4	1.437	1.527	0.924	0.735	PA reduced, MAP r^2, EKC, K1
5	1.059	1.418	0.511	0.622	EKC, K1
6	0.745	1.323	0.285	0.521	None

Note. PA = parallel analysis with 2,000 random data sets (n = 100, p = 19); MAP = minimum average partial test; EKC = empirical Kaiser criterion; K1 = eigenvalue greater than one. Number of factors kept: PA full matrix 1 (2 with the mean cut-off), PA reduced matrix 4, MAP r^2 4, MAP r^4 1, EKC 5, K1 5. For the digital strategic orientation block, all methods kept 3 factors.

The methods for deciding the number of factors did not agree for the IEAC block (Table 6). Parallel analysis on the full matrix with the 95th percentile cut-off kept only one factor, because the second eigenvalue (1.757) was slightly below its reference value (1.809). With the mean cut-off, it kept two. Parallel analysis on the reduced matrix kept four factors, and so did the squared version of the MAP test. The fourth-power version of the MAP test kept one factor. The EKC and the eigenvalue-greater-than-one rule kept five factors. In short, none of the simulation-based methods kept the five factors proposed in P1 and P2.

We interpreted this disagreement with three considerations. First, the first eigenvalue (7.083) was much larger than the second, which points to a strong general factor. This pattern is compatible with IEAC as a higher-order construct, but equally with a single general factor of digital activity. Under these conditions, parallel analysis on the full matrix tends to keep too few factors, while the reduced-matrix version is more accurate (Crawford et al., 2010; Lim & Jahng, 2019). Second, the proposed factors have only three items each and are correlated. This is the condition where the EKC works better than parallel analysis (Braeken & van Assen, 2017). Third, the one-factor solution does not make sense in substance. Item loadings on the single factor ranged only from 0.33 to 0.79, and the communality of DMC3 was only 0.11. For these reasons, the five-factor solution is reported first, because it corresponds to the propositions registered in advance and gave the simplest structure. It is treated as a

description of these data, not as evidence favoring P1 over the one-factor, four-factor, or mixed alternatives. We report the four-factor solution alongside it as the closest competitor. This decision is provisional. Auerswald and Moshagen (2019) showed that disagreement among methods signals factors that are hard to detect, which may require a sample of up to 500 respondents. For the digital strategic orientation block, all methods agreed on three factors.

Because the items are ordinal, the IEAC block was re-analyzed with polychoric correlations. These were slightly higher than the Pearson correlations (mean 0.36 versus 0.33), and the first eigenvalue rose to 7.63. Parallel analysis based on polychoric eigenvalues, with 100 random data sets that kept each item's observed distribution, retained one factor on the full matrix with the 95th-percentile cut-off (three with the mean cut-off) and four on the reduced matrix (five with the mean cut-off). The ordinal analysis therefore reproduced the disagreement rather than resolving it. On the polychoric matrix, the five-factor solution explained 61.7 percent of the common variance, every item again loaded most strongly on its intended factor (primary loadings 0.61 to 0.88; largest cross-loading 0.27), and the pattern matched the Pearson solution closely (Tucker's congruence coefficients 0.997 to 1.000). The four-factor polychoric solution again merged the two finance sides. The clean pattern is thus not an artifact of treating ordinal responses as continuous, but its robustness to the correlation type does not make it the correct number of factors, nor does it turn the pattern into psychometric evidence, given the response-quality results.

4.5 Factor Solutions for the Provisional IEAC Item Pool

Table 7. Pattern matrix, *principal axis factoring* with promax rotation, IEAC block

Code	F1	F2	F3	F4	F5	Largest cross-loading	h^2
DMC1	0.68					0.16 (F3)	0.59
DMC2	0.63					0.25 (F4)	0.54
DMC3	0.79					0.13 (F2)	0.58
DMC4		0.76				0.15 (F4)	0.61
DMC5		0.65				0.16 (F5)	0.55
DMC6		0.80				0.11 (F1)	0.63
DFC1			0.74			0.19 (F2)	0.57
DFC2			0.78			−0.17 (F2)	0.59
DFC3			0.64			0.06 (F4)	0.52
DFC4				0.71		0.16 (F5)	0.63
DFC5				0.71		−0.17 (F5)	0.45
DFC6				0.59		0.11 (F5)	0.45
IC1					0.75	0.06 (F1)	0.54
IC2					0.76	0.08 (F3)	0.53
IC3					0.67	0.20 (F2)	0.60
IC4					0.73	0.16 (F2)	0.63
IC5					0.61	0.15 (F3)	0.63
IC6					0.85	−0.19 (F3)	0.58
IC7					0.69	0.07 (F3)	0.48

Note. Loadings below 0.32 are left blank. F1 = DMC exploitation; F2 = DMC exploration; F3 = DFC exploitation; F4 = DFC exploration; F5 = improvisation capability. h^2 is the communality.

The five-factor solution (Table 7) explained 56.3 percent of the common variance before rotation. Every item loaded on its intended factor, with main loadings between 0.59 (DFC6) and 0.85 (IC6). No cross-loading reached 0.32. The largest cross-loading was DMC2 on the DFC exploration factor (0.25). The gap between the main loading and the largest cross-loading was at least 0.38, and communalities ranged from 0.45 (DFC5 and DFC6) to 0.63 (DMC6, DFC4, IC4, and IC5). No items were removed. This clean pattern is an output of the procedure on the current pool and data; it is not read as evidence that the five dimensions exist.

The four-factor solution, kept by parallel analysis on the reduced matrix and by the MAP test, explained 52.6 percent of the common variance. In this solution, the two marketing sides stayed separate, but all six finance items merged into one factor with loadings from 0.44 to 0.74. Two finance exploration items cross-loaded on the improvisation factor: DFC4 (0.26) and DFC6 (0.20). IC5 cross-loaded on the finance factor (0.27). This is not a pure structure by area as in P4. It is a mixed structure, with separate sides in marketing and merged sides in finance.

Table 8. Correlations between factors, IEAC block

	F1	**F2**	**F3**	**F4**	**F5**
F1 DMC exploitation	1.00				
F2 DMC exploration	0.29	1.00			
F3 DFC exploitation	0.37	0.38	1.00		
F4 DFC exploration	0.40	0.34	0.60	1.00	
F5 Improvisation capability	0.39	0.52	0.54	0.57	1.00

The correlations between factors ranged from 0.29 to 0.60 (Table 8). The correlation between the two sides in marketing (0.29) was much lower than in finance (0.60). The improvisation factor correlated 0.39 to 0.57 with the other four factors.

4.6 Factor Structure of the Digital Strategic Orientation Block

Table 9. Pattern matrix, *principal axis factoring* with promax rotation, digital strategic orientation block

Code	**F1 Customer**	**F2 Competitor**	**F3 Technology**	**h^2**
CUST1	0.63			0.59
CUST2	0.71			0.48
CUST3	0.63			0.44
CUST4	0.63			0.40
CUST5	0.78			0.59
COMP1		0.67		0.47
COMP2		0.72		0.46
COMP3		0.67		0.50

Code	F1 Customer	F2 Competitor	F3 Technology	h^2
COMP4		0.47		0.32
COMP5		0.65		0.48
TECH1			0.72	0.59
TECH2			0.74	0.53
TECH3			0.72	0.53
TECH4			0.73	0.55
TECH5			0.72	0.52

Note. *Loadings below 0.32 are left blank. Solution with all fifteen items, before COMP4 was removed. h^2 is the communality.*

The three-factor solution with fifteen items (Table 9) explained 49.7 percent of the common variance. Customer, competitor, and technology orientation items each loaded on their own factor. Main loadings were 0.63 to 0.78 for customer, 0.47 to 0.72 for competitor, and 0.72 to 0.74 for technology. One item did not meet the criteria. COMP4 loaded 0.47 on the competitor factor and 0.30 on the technology factor, so the gap was only 0.17, and its communality was 0.32. Following the criteria set before the analysis, COMP4 was removed. After removal, the three-factor solution with fourteen items explained 51.0 percent of the common variance. All main loadings were between 0.56 and 0.82, no cross-loading was above 0.22, communalities ranged from 0.41 to 0.61, and correlations between factors ranged from 0.37 to 0.52.

4.7 Internal Consistency (Provisional)

Table 10. Reliability, average variance extracted (AVE), and corrected item-total correlations (CITC)

Subscale	Number of items	Standardized α	CR	AVE	CITC range	Lowest CITC item
DMC exploitation	3	0.76	0.76	0.52	0.57 to 0.62	DMC3
DMC exploration	3	0.80	0.80	0.58	0.64 to 0.66	DMC6
DFC exploitation	3	0.77	0.77	0.53	0.60 to 0.62	DFC2
DFC exploration	3	0.74	0.74	0.49	0.54 to 0.61	DFC5
Improvisation capability	7	0.90	0.90	0.55	0.64 to 0.74	IC7
Customer orientation	5	0.82	0.82	0.49	0.57 to 0.68	CUST4
Competitor orientation	4	0.78	0.78	0.47	0.57 to 0.59	COMP3
Technology orientation	5	0.85	0.85	0.54	0.65 to 0.69	TECH2

All subscales reached a standardized alpha of at least 0.70 (Table 10). The lowest values were for DFC exploration (α = 0.74; CR = 0.74). This was also the only IEAC subscale with an average variance extracted below 0.50 (0.49). In the digital strategic orientation block, the average

variance extracted for customer orientation (0.49) and competitor orientation (0.47) was also slightly below 0.50. All corrected item-total correlations were above 0.30, with the lowest value of 0.54 for DFC5. Before COMP4 was removed, its corrected item-total correlation was 0.42 and the alpha of the competitor orientation subscale was 0.78, so removing it did not lower reliability.

These values describe internal consistency in a pilot whose factor structure is unresolved. Composite reliability and AVE were computed from one-factor solutions per subscale, and both presuppose a measurement model that only confirmatory analysis on the verified sample can establish (Cheung et al., 2024). They are therefore not read as evidence of convergent validity. Three AVE values fell below 0.50, for DFC exploration, customer orientation, and competitor orientation, and construct validity remains unestablished.

4.8 Descriptive Correlations with Anchor and Companion Measures

Table 11. Correlations between composite scores, validation anchor items, and global rating items

	1	2	3	4	5	6	7	8	9	10	11
1. DMC exploitation											
2. DMC exploration	0.29										
3. DFC exploitation	0.33	0.35									
4. DFC exploration	0.36	0.31	0.50								
5. Improvisation capability	0.38	0.49	0.47	0.51							
6. Customer orientation	−0.07	0.08	0.02	0.05	0.06						
7. Competitor orientation	−0.01	0.08	0.03	0.15	−0.02	0.44					
8. Technology orientation	0.00	0.06	0.14	0.22	0.08	0.41	0.31				
9. VAL1	0.43	0.43	0.69	0.58	0.36	0.03	0.11	0.16			
10. VAL2	0.50	0.54	0.54	0.52	0.52	0.11	0.09	0.12	0.52		
11. IEAC_GLB	0.39	0.55	0.48	0.51	0.50	0.13	0.12	0.22	0.48	0.59	
12. DSO_GLB	−0.04	0.08	−0.09	−0.05	−0.04	0.44	0.42	0.47	−0.03	0.05	0.07

Note. *n = 100. Composite scores are equally weighted sums of standardized items. With n = 100, a correlation of 0.20 or more is significant at the 0.05 level (two-tailed).*

Based on composite scores (Table 11), the correlation between the two sides was 0.29 for marketing and 0.50 for finance. A correlation below a conventional threshold does not by itself justify a difference score (Edwards, 2001), so no difference score is formed here; polynomial regression with response surface analysis is preferred, as discussed later. The four side scores and the improvisation score correlated 0.36 to 0.69 with the validation anchor items and 0.39

to 0.55 with the global IEAC rating item. The three digital strategic orientation scores correlated 0.42 to 0.47 with the global digital strategic orientation rating item, while these five scores were not related to that item (−0.09 to 0.08).

The validation anchor items did not fully behave according to their area. VAL1 was designed as the anchor for marketing, but it correlated most strongly with DFC exploitation (0.69) and only 0.43 with the two marketing sides. VAL2 was designed as the anchor for finance, but it correlated about equally with all four sides (0.50 to 0.54). Both anchor items therefore behaved more like indicators of general digital activity than like anchors for a specific area. Whether this reflects the anchors, the subscales, or the response quality problems reported above cannot be decided from these data.

A combined analysis of all 34 items with eight factors reproduced all of the groupings above. Every item loaded most strongly on its intended factor. Two cross-loadings touched the threshold: DMC2 on the DFC exploration factor (0.32) and COMP4 on the technology factor (0.33). Correlations between the five factors of the IEAC block and the three digital strategic orientation factors ranged from −0.10 to 0.17.

The finding that needs the most attention is the relationship between the two blocks. The overall IEAC composite score, computed only as a descriptive check and not as a recommended IEAC score, correlated only 0.10 with the digital strategic orientation composite score, and the two global rating items correlated 0.07. Of the 285 item correlations across the two blocks, the mean was 0.035 with a standard deviation of 0.085, and 33 percent were negative. This spread cannot be told apart from what we would expect if the true correlation were zero with n = 100, where the sampling standard deviation is about 0.10.

4.9 Discussion

4.9.1 Rival Structures That Remain Plausible

Two boundaries govern everything in this section. The item pool has not been content-validated, so any factor solution describes the items that were written, not IEAC as defined. The responses also cannot be assumed to follow item content, so even a clean solution with low cross-loadings is not psychometric evidence in the ordinary sense. Within these boundaries, the pilot does not establish the symmetric four-side structure that the strongest version of P1 implies. Retention methods supported one, four, or five factors. The five-factor solution matched the proposed sides only descriptively, while the four-factor solution kept the marketing sides apart and merged the finance sides; the pure structure by area in P4 did not appear. Several rival structures therefore remain plausible, and none can be preferred on these data.

Three patterns in these data are recorded only as hypotheses for complete replication, because each was generated in a compromised pilot dataset. First, the marketing sides correlated 0.29 and stayed apart in every solution, whereas the finance sides correlated 0.60 and merged when one fewer factor was extracted. The construct definition anticipated this asymmetry, since financial exploration in a micro enterprise usually builds on the recording and payment routines that make up exploitation (Su et al., 2022; Sumail et al., 2026). Agreement with an expectation is still not evidence when responses may not reflect item content. Second, the improvisation items formed a factor of their own, discussed below. Third, if separation of the

sides at the owner level is reproduced, it would extend firm-level evidence that exploration and exploitation can be distinguished (He & Wong, 2004; Liu et al., 2026) to businesses without separate units. None of these patterns is interpreted further here.

One modeling consequence holds whatever replication shows. Where the two sides of a domain correlate highly, a difference-based ambidexterity score loses reliability, so polynomial regression with response surface analysis, which never forms a difference score, is the safer choice (Edwards, 2001; Rosing & Zacher, 2017).

The strong first eigenvalue admits two readings. In one, the four side dimensions share a higher-order capability, reflective or composite, while remaining distinct at the first order, with improvisation as a correlated enabler outside it. In the other, most item variance reflects a general tendency to report digital activity, which in these data may itself be a response artifact. These readings, together with the mixed and domain structures, can be separated only by a confirmatory comparison of the rival structures in Table 12, run on a content-validated pool and a verified sample.

Fit comparisons alone will not settle the matter, because bifactor models often fit better than their rivals for statistical reasons. Four further kinds of evidence would distinguish genuinely separate capabilities from a broad tendency toward digital business activity. First, bifactor indices: when the explained common variance and hierarchical omega of the general factor are high and the specific factors keep little reliable variance, subscale scores add little beyond a general score (Rodriguez et al., 2016). Second, discriminant evidence between the sides within each domain, using the criteria summarized by Cheung et al. (2024). Third, differential correlates. Exploration should relate more strongly than exploitation to records of channels or financial services tried for the first time in the past year, whereas exploitation should relate more strongly to signs of routine refinement, such as repeat-purchase rates. A general activity factor predicts no such difference. Fourth, invariance: if the sides are capabilities, the structure should hold across micro and small enterprises and across owners with low and high digital experience, tested through configural, metric, and scalar steps (Putnick & Bornstein, 2016).

Table 12. Rival structures to be compared on the independent sample

Model	Specification	Evidence that would favor it
M1 General factor	All IEAC items load on one digital-activity factor	Fit close to the multidimensional models; high explained common variance in M6; no differential correlates of the sides
M2 Domain model (P4)	Two factors: digital marketing and digital finance	Sides within each domain cannot be separated; side correlations near unity in both domains
M3 Mixed model	Separate marketing sides; one merged finance factor	High finance side correlation with low marketing side correlation, replicating the pilot four-factor pattern
M4 Correlated sides (P1, P2)	Four correlated side factors, with improvisation as a separate factor	Discriminant evidence between sides in both domains; improvisation items do not load on side factors

Model	Specification	Evidence that would favor it
M5 Second-order IEAC	Four side factors loading on a higher-order IEAC factor; improvisation outside	M4 conditions plus adequate higher-order loadings; establishes statistical commonality only, and a single score also requires evidence that it captures ambidexterity rather than general digital activity
M6 Bifactor	A general factor plus four specific side factors	Specific factors keep reliable variance beyond the general factor, which supports reporting side scores
M7 Reflective-formative IEAC	Four reflective side factors combined into a weighted composite higher-order IEAC (two-stage estimation or confirmatory composite analysis); improvisation outside	Non-interchangeable sides, as argued in the construct definition; acceptable fit of the composite model (Schuberth et al., 2018); side weights that differ in line with the profile interpretation

Note. *All models are estimated on the holdout half of the verified sample; improvisation is modelled as a separate correlated factor in M1 to M7. All models are estimated with methods for ordinal indicators.*

No single overall IEAC score should be computed or recommended at this stage. Support for M5 over M1 and M6 would establish statistical commonality, and support for M7 would justify a weighted profile, but neither would show that a score captures ambidexterity rather than general digital activity. Until both questions are settled, the four side scores and the improvisation score should be reported separately, and any ambidexterity index should be formed only within a domain where the sides have been shown to be distinct.

The second question concerns what an IEAC score should measure. Ambidexterity is not simply being active on both sides; it concerns the joint pursuit and balance of competing exploitation and exploration demands. Cao et al. (2009) separated a combined dimension, the joint magnitude of the two sides, from a balance dimension, their relative match, and found that balance was more beneficial to resource-constrained firms. A reflective general factor captures at best the combined magnitude, and in these data it may capture only a general tendency to report digital activity. An owner who reports frequent activity on every item would receive a high general score without showing that she manages the tension between refining and searching. The future scoring model will therefore follow four routes. First, polynomial regression with response surface analysis will enter exploitation and exploration as separate predictors of outcomes, so that the effects of balance and of joint magnitude can be read from the surface without forming a difference score (Edwards & Parry, 1993). Second, latent interactions between the sides will test whether exploration pays off more when exploitation is also high. Third, person-centered profiles estimated with latent profile analysis (Spurk et al., 2020) will show whether owners high on both sides form a distinct group, and whether marketing and finance profiles coincide. Fourth, the validation anchors will be rewritten as domain-specific joint items that ask directly about pursuing both sides at once. Where a bifactor general factor is retained, these analyses will be repeated with the general factor controlled, so that ambidexterity is not confounded with overall digital activity.

4.9.2 The Role of Improvisation Capability

In the pilot data the seven improvisation items formed a factor of their own (loadings 0.61 to 0.85; α = 0.90), which matches P2 descriptively. Under the same two boundaries, this is a pattern to replicate, not support for P2.

This separation fits the conceptual boundary set by Ciuchta et al. (2021), who placed improvisation in the meeting of planning and doing and in spontaneity, not in a specific business area. Tariq et al. (2026) and Chen et al. (2023) treat improvisation as a stand-alone dynamic capability that affects innovation. Hultman et al. (2022) remind us that the dimensions of improvisation do not have equal effects. Treating it as one dimension in this study is therefore a deliberate simplification that should be tested again on a larger, verified sample.

If the separation replicates, the likely reason lies in the way the items are written. Improvisation is a way of acting, not an area of action. The improvisation items ask how the owner responds to sudden problems and how she uses what is available, without saying whether the problem is about marketing or finance. Because they do not share content with the two digital areas, these items do not pick up the same variance as the marketing and finance items.

Being separate does not mean being unrelated. The improvisation factor correlated 0.39 to 0.57 with the four side factors, and in the four-factor solution two finance exploration items cross-loaded on the improvisation factor. If replicated, this pattern would fit the role of improvisation as an enabling mechanism. It also shows that finance exploration items that ask about trying things with uncertain results, especially DFC4 and DFC6, share some spontaneity with the improvisation items. The wording of these two items should be reviewed before confirmatory testing.

The implication for future modeling is clear. Improvisation capability should be modeled as a mediator or moderator in the relationship between digital capability and performance, not as a part of the ambidexterity score. This also avoids the circular reasoning that would appear if improvisation were treated as a third side. Its enabling role can also be tested directly on verified data. If improvisation enables switching, it should moderate how the two sides relate to later outcomes, or predict the balance between them, while its items stay off the side factors. If instead its items begin to load on the side factors, the separation of improvisation from IEAC would have to be reconsidered.

4.9.3 The Structure of Digital Strategic Orientation

The digital strategic orientation items formed three factors that match the customer, competitor, and technology dimensions. This matches P3 descriptively after one competitor item was removed, subject to the same two boundaries as the IEAC block. Correlations between factors ranged from 0.37 to 0.52.

This finding should be read alongside the source of the instrument. Yu and Moon (2021) treated the three orientations as three separate predictors, and competitor orientation had no significant effect on digital competence in their model. In these data, the three dimensions appeared separate with moderate correlations. This result does not rule out a higher-order specification, although its formative combination has not yet been tested. The competitor

dimension was the weakest, with an average variance extracted of 0.47 and one item removed. This matches the weakness of this dimension in the original source. We stress again that exploratory factor analysis only checks the reflective structure at the first level. Treating digital strategic orientation as a second-order reflective-formative construct departs from the source and needs its own test with a two-stage procedure.

4.9.4 The Relationship between IEAC and Digital Strategic Orientation

The IEAC composite score was almost unrelated to digital strategic orientation (r = 0.10), and the global ratings of the two constructs were also unrelated (r = 0.07). For discriminant validity, this looks like good news. For nomological validity, it is a problem. Nomological validity means that a construct relates to other constructs in the way theory predicts. Digital strategic orientation is expected to come before digital capability: it has been positively linked to digital competence (Yu & Moon, 2021) and to digital capabilities (Zhang et al., 2025), and studies of small and medium enterprises place digital orientation alongside digital capability as joint drivers of digital innovation and transformation (Khin & Ho, 2019; Rupeika-Apoga et al., 2022). A positive link has also been found between market orientation and digital marketing capability in small businesses in emerging markets (Hidayati et al., 2025).

A correlation of almost zero is also unusual from a methods point of view. Both blocks were answered by the same person in one session, with similar answer formats, about the same digital business behavior. In such conditions, common method variance usually pushes correlations between constructs upward. Common method variance is the shared bias that comes from measuring everything in the same way at the same time. Re-analyses of past studies put this upward push at around 0.10 (Malhotra et al., 2006), and the push is largest when the true correlation is low (Baumgartner et al., 2021). The fact that one third of the item correlations across blocks were negative, and that their spread was no wider than sampling error, needs an explanation.

Three explanations must be separated before this result can be interpreted. The first is substantive. Among women owner-managers, digital strategic orientation may still be an attitude that has not yet turned into behavior. This fits the gap between capacity and performance reported by Pranitasari, Harini, et al. (2026). The second is about the instrument. Digital strategic orientation items use an agreement scale, while digital capability items use a frequency scale, and different scales can reduce common method variance. However, this explanation is not enough, because the improvisation items also use an agreement scale, yet their composite score correlated 0.38 to 0.51 with the four digital capability sides. The third is about data quality. Paid online panel data are open to careless and even fake answers, and low-quality answers are known to distort correlations between constructs (Chandler et al., 2020; Ward & Meade, 2023). The response quality results make the third explanation the most parsimonious, but they do not establish it: item means did not follow item content, and the profile answers were internally inconsistent. Under these conditions, both the near-zero correlation between the blocks and the clean structure within each block may be artifacts of the data source, and the factor structure reported above cannot yet be read as a property of the instrument.

The anchor results call for the same restraint. VAL1, written as a marketing anchor, related most strongly to financial exploitation. One reading is substantive: in a micro enterprise, refining marketing may depend on knowing which products earn money, so marketing and financial routines overlap in practice. A second reading is that the anchors capture a general disposition rather than domain-specific behavior. A third is that, like the near-zero correlation between the blocks, the pattern reflects responses not driven by item content. None of these readings is adopted here. Verified data can separate them by testing whether the near-zero correlation persists once all quality checks are passed, whether it persists when orientation and capability are measured at different times, and whether anchors rewritten as concrete behaviors align with their intended domain. For this reason the relationship is no longer treated as an exploratory correlation. The verified stage registers it as a falsifiable prediction with a stated rejection criterion, and if IEAC remains almost unrelated to this theoretically proximal antecedent in verified data, the construct definition or the measurement model will have to be reconsidered.

4.9.5 Theoretical Implications

The empirical contribution of this study is primarily methodological. A clean exploratory solution, with low cross-loadings and reproduced on polychoric correlations, emerged from data whose responses cannot be assumed to follow item content, which shows concretely why response-quality verification and content validation must precede structural interpretation. Beyond this lesson, the study offers three theoretical contributions, all at the level of a candidate construct architecture rather than of validated measurement. First, it moves ambidexterity down from the level of organizational units to the level of the owner-manager's behavior within specific business areas. This answers the call by Wilden et al. (2018) to study the microfoundations of exploration and exploitation. It also addresses a practical problem: owners who run everything themselves cannot answer questionnaires that assume separate units.

Second, this study brings together two streams of literature that have so far been separate, digital marketing capability and digital financial capability, in one measurement framework. This is not just for convenience. In a small business, the two areas compete for the same attention and money, so measuring only one of them risks misjudging the owner's overall capability. Table 1 makes explicit what measures of adoption, literacy, competence, and single-domain ambidexterity leave out, which gives later studies a basis for testing whether IEAC adds explanatory power beyond them.

Third, this study treats proof that the two sides are separate as a requirement, not as an extra. Most studies of ambidexterity in small businesses go straight to forming a difference or product score without first checking whether the two sides are actually separate in the population. The pilot illustrates the point without settling it: in these compromised data, the marketing sides appeared separate while the finance sides correlated 0.60 and merged in the simpler solution. If this pattern holds on verified data, checking separation would change how the ambidexterity score is formed, even within one instrument.

4.9.6 Practical Implications

These implications are conditional, and on present evidence they apply only to owner-managers of urban micro enterprises who already use digital channels; the instrument cannot identify owners who have not yet adopted them. The instrument is not yet ready to guide interventions, select program participants, or compare groups of businesses. Those uses require the content validation, verified-sample confirmation, and invariance tests set out above, together with evidence that IEAC scores relate to outcomes such as adaptability, innovation, and business resilience (Iborra et al., 2022; Su et al., 2022). What follows describes the uses the framework is designed for once that evidence exists.

For people who design digital mentoring programs, a validated version of this instrument would allow a sharper picture than adoption measures. Two business owners may both be listed as users of digital channels. Yet one may simply repeat the same routine again and again, while the other improves that routine and also tests new things. These two owners need different support. Owners who are weak on the exploitation side need help with reading data and improving processes. Owners who are weak on the exploration side need room to experiment with risks they can afford.

For organizations that measure program impact, a validated version would offer an indicator that is closer to capability than account ownership or frequency of use. Adoption measures quickly reach their ceiling, because almost all participants eventually open an account. Capability measures could still tell participants apart after adoption becomes universal.

5. Conclusion

Ambidexterity in micro and small enterprises needs a different definition from the one used for large companies, because exploitation and exploration are done by the same person and cannot be split into separate units. This study proposed Integrated Entrepreneurial Ambidexterity Capability as a candidate architecture: four side-by-domain capabilities in digital marketing and digital finance, a higher order whose reflective or composite form is still open, and improvisation as an adjacent enabling mechanism outside the score. It wrote an initial item pool and rehearsed the analytic procedure on it. The pilot did not identify IEAC structurally. Retention methods supported one to five factors, the five-factor solution matched the proposed sides only descriptively, the finance sides merged in the four-factor solution, and IEAC was almost unrelated to digital strategic orientation. Two boundaries apply to all of these results. The pool has not been content-validated by independent experts and owners, and the responses cannot be assumed to reflect item content, because the item means were more uniform than an ordinal sensitivity analysis allows and the profile answers were internally inconsistent. The strongest defensible result is that several rival structures remain plausible and must be adjudicated on an independent, verified sample after content validation. The evidence concerns digitally active women owner-managers of predominantly urban micro enterprises; it says almost nothing about small enterprises, low-adoption firms, or less urban owners.

Beyond the methodological lesson, the theoretical contribution of this study lies in moving ambidexterity to the level of the owner-manager's behavior within business areas, in bringing

together two separate streams of digital capability research, and in treating proof of separation between the two sides as a requirement for modeling. In practice, once validated on verified data, this instrument can help program designers tell apart owners who are weak on the exploitation side from those who are weak on the exploration side. These two groups need different support, and adoption measures have not been able to tell them apart. Until then, the instrument should not be used for assessment, policy design, or comparisons across business groups, and no single overall IEAC score should be reported.

This study has seven limitations. First, the sample of 100 respondents is a pilot sample, while the four IEAC factors have only three items each. According to MacCallum et al. (1999), this condition requires a larger sample. Second, the structure found is exploratory, the methods for deciding the number of factors did not agree, and a factor solution from one sample does not guarantee the same result in another sample. Third, all data came from one source at one point in time, so common method variance cannot be ruled out. Fourth, the sample was largely urban, relatively highly educated, and concentrated in micro enterprises (96 percent). Owners who do not use digital channels were excluded by design, which restricts the range of the capability continuum, and ownership share, number of workers, and business age were absent from the dataset, so the pilot offers no basis for claims about small enterprises, low-adoption firms, or less urban owner-managers. Fifth, treating digital strategic orientation as a higher-order construct departs from the original source and has not yet been tested at the formative level. Sixth, the item means were more uniform than an ordinal sensitivity analysis allows, and the profile answers were internally inconsistent, although the diagnostic behind the first finding is author-developed and not externally validated. The factor structure and the almost zero correlation between IEAC and digital strategic orientation may therefore reflect the data source rather than the instrument. Seventh, content validity was reviewed only by the research team; it has not been rated by independent experts, and coverage of the full meaning of each dimension has not been tested (Table 2).

Three directions for future research follow directly from these limitations. Collecting new data through verifiable channels, with attention checks and survey paradata, and confirming the structure with confirmatory factor analysis on that sample follows content validation and should not be delayed beyond it. This test should compare the seven rival structures in Table 12, from a single general factor to second-order, bifactor, and composite higher-order models. Testing measurement invariance across business size groups will also test the idea that only small firms can be ambidextrous while micro firms are in survival mode. Finally, tests of predictive validity for business performance should use an approach that does not form a difference score, so that the conclusions do not depend on reliability assumptions that are hard to meet. In addition, a content validity rating by at least six independent experts should be carried out, so that item revisions are based on judgments from outside the research team. The order of these steps matters. Content validation by independent experts and owners comes first, followed by a verified sample collected under the registered protocol, the comparison of rival structures in Table 12, invariance testing, and only then tests of whether IEAC relates to adaptability, innovation, and resilience. Within this sequence, the relationship between IEAC and digital strategic orientation is tested as a registered, falsifiable prediction.

5.1 Data and Materials Availability

The item list with its sources, the analysis procedure, and the content-review record are provided as Supplementary Appendices A to C. The Python code that reproduces every statistic in the Results from the item-level data, including the polychoric re-analysis and the sensitivity analysis of Check 3, is provided as a supplementary file. The anonymized item-level data are available from the corresponding author on reasonable request.

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