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Article

Human capital, adaptive capability, and innovation thresholds in Philippine MSME bakeries

Jupert Jasser G. Abellana[1*], Albert A. Alonzo[2], Metonia M. Gonzales[3]

[1]Department of Business and Innovation, College of Economics, Business and Accountancy, Mindanao State University–Iligan Institute of Technology, Iligan City, Philippines
[2]Department of Accountancy and Business Management, College of Business and Information Technology, Mindanao State University at Naawan, Naawan, Misamis Oriental, Philippines
[3]Business Administration Department, Bukidnon State University - Cabanglasan Campus, Cabanglasan, Bukidnon, Philippines

*__Corresponding author:__ Jupert Jasser G. Abellana; jupertjasser.Abellana@g.msuiit.edu.ph

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Abstract: Resource-constrained bakery enterprises must decide which capabilities to develop and which capability gaps may constrain innovation. Drawing on the microfoundations of dynamic capabilities and human-capital theory, this study combines bootstrapped multiple regression and necessary condition analysis (NCA) using item-level survey data from 227 micro, small and medium-sized bakeries in Northern Mindanao, Philippines. Five capability indices —entrepreneurial experience, family background, related education/training, agility/adaptability, and technological complementarity—were examined in relation to process, product and technological innovation. Separate regressions controlled for years of operation and used 5,000 bootstrap resamples; ceiling envelopment–free disposal hull (CE-FDH) NCA used 10,000 permutations. False-discovery-rate adjustments covered 15 focal tests for each method. Process innovation ($R^2 = .389$) was positively associated with agility/adaptability ($\beta = 0.561$) and family background ($\beta = 0.211$); NCA identified both indices and technological complementarity as empirical bottlenecks. At 80% of the observed process-innovation range, the corresponding minimum input levels were 26.7% , 20.0% and 53.3% of their observed ranges, respectively. Product innovation ($R^2 = .245$) was positively associated with technological complementarity ($\beta = 0.353$), but no individual capability met the NCA criterion for necessity. Technological innovation ($R^2 = .163$) was positively associated with related education/training ($\beta = 0.229$) and technological complementarity ($\beta = 0.208$); no NCA result survived multiplicity correction. These findings distinguish conditional average associations from observed capability floors and suggest that development priorities vary across innovation outcomes. Cross-sectional bottlenecks should not be interpreted as universal causal thresholds.

Keywords: dynamic capabilities; entrepreneurial learning; family-derived knowledge; workforce development; technological complementarity; process improvement; necessary condition analysis; small food manufacturers

1. Introduction

Resource constraints require bakery managers to choose among worker training, production reorganization, family-derived knowledge and machinery integration. Research often treats these capabilities as additive contributors to innovation: higher capability levels are expected, on average, to accompany better outcomes. Managers also face a question about constraints: can a bakery achieve high process innovation with few adaptive routines, even when other resources are available? A regression coefficient alone cannot answer

this question. Regression summarizes conditional average associations, whereas necessary condition analysis (NCA) examines whether high observed outcomes are absent below a minimum input level (Dul, 2016; Bokrantz & Dul, 2023).

This distinction is particularly relevant to food-sector enterprises, where innovation often occurs without formal R&D units. Avermaete et al. (2004) highlighted firm and network determinants of product and process innovation in small food manufacturers. The Oslo Manual also distinguishes product changes from changes in business processes (OECD/Eurostat, 2018). In bakeries, new product formulations, revised production workflows and implemented technological solutions may draw on overlapping but distinct knowledge and resources. Combining these outcomes may obscure the conditions associated with each (Saunila, 2020).

Dynamic-capabilities theory explains innovation through sensing, seizing and resource reconfiguration (Teece et al., 1997; Teece, 2007). Research on microfoundations locates these organizational capabilities in individuals, routines and relationships (Felin et al., 2012). Human-capital theory and absorptive-capacity research likewise emphasize learning and relevant prior knowledge (Becker, 1964; Cohen & Levinthal, 1990). These perspectives do not imply that experience, family-derived knowledge, formal training, agility and technology fit play identical roles across innovation domains. A positive average association does not establish that a resource is indispensable.

Previous research in Northern Mindanao provides a basis for this analysis. Abellana and Alonzo (2025a) examined bakery innovation and distribution strategies, while a study of 113 bakery enterprises linked entrepreneurial resources and distribution channels to growth (Alonzo & Abellana, 2025b). A subsequent analysis of 227 bakery respondents examined product and process innovation as predictors of growth and entrepreneurial experience as a moderator (Abellana, et al., 2026). These studies address the business context and consequences of innovation, but do not jointly examine the conditional associations and empirical ceiling restrictions of five capability indices across three innovation outcomes. Related regional MSME research reports underinvestment in people development and productive assets (Alonzo et al., 2025; Alonzo & Abellana, 2026), while agribusiness research highlights organizational conditions for digital adoption (Alonzo & Abellana, 2025). Together, this work motivates closer examination of capability allocation.

This study examines how five entrepreneurial and organizational capability indices relate to three bakery innovation outcomes and whether any indices exhibit sample-specific necessity patterns. Bootstrapped multiple regression estimates conditional associations, while CE-FDH NCA examines whether high observed innovation outcomes require a minimum input level within the sample. The aim is to distinguish capability roles across outcomes rather than establish a universal resource ranking. Given the observational design, necessity refers to empirical ceilings rather than demonstrated causal prerequisites. See **Figure 1**.

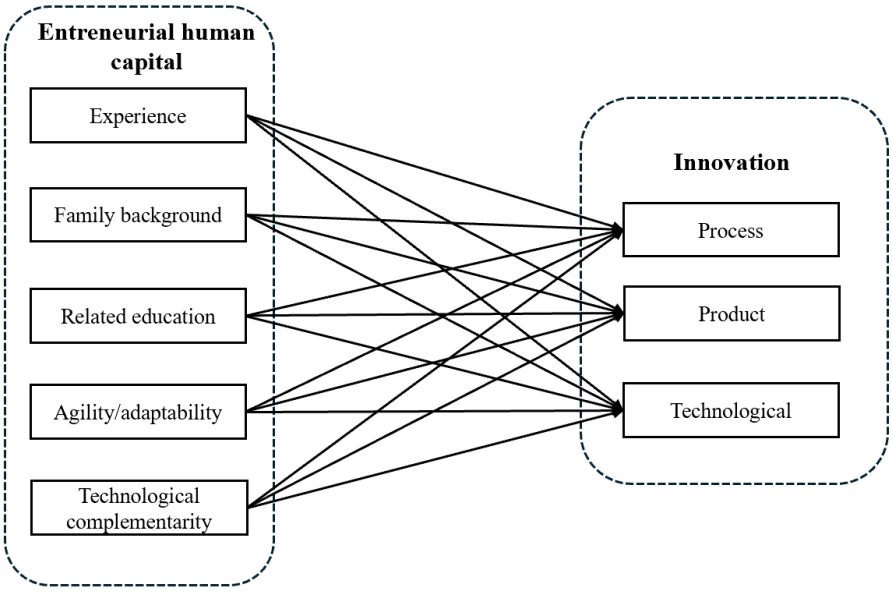

Figure 1. Conceptual framework of the study

Note. The original questionnaire groups experience, family background, related education, agility/adaptability and technological complementarity as entrepreneurial human-capital attributes. In the present analysis these are treated as five separate reported capability indices, including adaptive routines and technology fit; the grouping does not equate family background with family ownership or imply that all five indices directly measure employees' skills (Abellana, 2024).

2. Materials and methods

2.1 Research setting, sample and reuse disclosure

The study analyzes 227 complete bakery MSME survey records from Misamis Oriental and Lanao del Norte, Northern Mindanao, Philippines, collected from January to May 2024. Purposive recruitment targeted bakeries classified as micro, small or medium-sized enterprises under Department of Trade and Industry criteria, operating for at least five years, and represented by an owner or manager actively engaged in daily operations. The original study used direct visits, paper questionnaires and online forms when appropriate; an owner or manager supplied the assessment on behalf of the enterprise (Abellana, 2024; Abellana, et al., 2026). Among the 227 respondents, 90 identified as owners, 74 as managers and 63 as owner-managers; 138 bakeries were micro, 81 small and eight medium enterprises (Abellana, et al., 2026). The analytical file contains complete responses on all 40 focal items and years of operation, and no case was excluded. Each record was analyzed at the enterprise level.

This study reanalyzes the 227-case bakery survey used by(Abellana, et al. (2026) to examine product and process innovation in relation to business growth, including moderation by entrepreneurial experience. Here, process, product and technological innovation are treated as separate outcomes, and five capability indices are examined using multiple regression and NCA. The doctoral dissertation documenting instrument development, recruitment safeguards and consent materials reported a separate sample of 113 enterprises (Abellana, 2024; Abellana, & Alonzo, 2025b). The 113-case dissertation sample and the 227-case archive are therefore distinguished and are not combined or presented as identical. See **Table 1**.

Table 1. Years of operation in the recovered bakery dataset (N = 227)

Years of operation	n	%
5–10	184	81.1
11–20	32	14.1

Continued table:

Years of operation	n	%
More than 20	11	4.8

2.2 Measures and archived-score integrity

Eight construct scores were calculated from the forty original item columns: entrepreneurial experience (C1–C5), family background (C6–C10), related education/training (C11–C15), agility/adaptability (C16–C20), technological complementarity (C21–C25), process innovation (D1–D5), product innovation (D6–D10), and technological innovation (D11–D15). The originating questionnaire documents a four-point agreement scale (1 = Strongly Disagree; 2 = Somewhat Disagree; 3 = Somewhat Agree; 4 = Strongly Agree), with higher scores indicating greater agreement with the positively framed capability and innovation statements (Abellana, 2024). The 227-case analytical archive likewise contains item responses from 1 to 4. The arithmetic mean of each five-item block agrees exactly with its archived index in all records. No items in these eight original blocks require reverse scoring according to the documented questionnaire wording; no post-hoc recoding or item deletion was undertaken. The earlier 2026 growth-model publication describes a reduced 20-indicator, five-point specification; the present analysis instead follows the documented four-point questionnaire and its corresponding forty recorded item scores.

Because the analysis uses observed, equally weighted indices rather than a latent-variable model, internal consistency is reported descriptively (**Table 2)**. Cronbach's alpha ranged from .615 for agility/adaptability to .981 for process innovation. The relatively low agility/adaptability coefficient warrants cautious interpretation. The dissertation identifies C25 as "I can clearly explain technical information to both technical and non-technical audiences"; its corrected item–rest correlation within technological complementarity was −.055. D11 reads "The bakery uses automated mixing systems to improve the efficiency and consistency of its dough mixing process"; its corrected item–rest correlation within technological innovation was .139 (Abellana, 2024). Both statements are positively worded and were retained in their original 1–4 scoring direction. Their weak item–rest relationships may reflect differences between their specific content and the broader item blocks, although this interpretation remains tentative. All forty prespecified items and eight index definitions were retained.

Table 2. Descriptive statistics and internal consistency (N = 227)

Construct	Mean	SD	Min	Max	α
Entrepreneurial experience	2.359	0.993	1.0	4.0	.852
Family background	2.830	0.815	1.0	4.0	.753
Related education/training	2.025	0.742	1.0	4.0	.701
Agility/adaptability	2.317	0.660	1.0	4.0	.615
Technological complementarity	2.857	0.824	1.0	4.0	.716
Process innovation	2.337	1.252	1.0	4.0	.981
Product innovation	2.801	1.124	1.0	4.0	.963
Technological innovation	1.560	0.632	1.0	4.0	.780
Years of operation	8.621	5.434	5.0	40.0	—

Note. The eight construct scores equal their five-item arithmetic means exactly; α = Cronbach's alpha. The four response options follow the original questionnaire (Abellana, 2024). Years of operation is a single observed covariate (α not applicable). Technological innovation was right-skewed (sample skewness = 2.018).

2.3 Analytical strategy

Three ordinary least-squares multiple regressions modeled process, product and technological innovation separately. Each equation included all five capability indices and years of operation; all coefficients were standardized using full-sample standard deviations. Unstandardized OLS fitting was used for residual diagnostics. Five thousand case-resampling bootstrap replicates (random seed 20261017) provided percentile 95% confidence intervals and two-sided sign-tail bootstrap p-values using the plus-one correction. Cohen's f^2 compared the full model with a model excluding each predictor. Benjamini–Hochberg false-discovery-rate (FDR) correction was applied to the 15 focal capability associations, excluding the three prespecified years-of-operation controls. Variance inflation factors and Breusch–Pagan tests were examined; HC3 heteroskedasticity-robust standard errors were also calculated as sensitivity checks. Results are regressions on observed composites, not partial least squares structural equation modeling (PLS-SEM).

For the complementary NCA, ceiling envelopment–free disposal hull (CE-FDH) areas were calculated directly for the same 15 bivariate capability–innovation pairs. The ceiling effect d is the empty upper-left ceiling zone divided by the empirical predictor-by-outcome scope (Dul, 2016). Ten thousand independent permutations of the outcome values per pair (seed 20261018) yielded permutation p-values using a count-plus-one denominator of 10,001. Benjamini–Hochberg FDR correction was applied separately to these 15 tests. For NCA, years of operation is not conditioned upon: an empirical necessity ceiling represents a descriptive bivariate constraint, not a controlled regression effect. Bottleneck values are derived from the observed 1–4 score ranges for target outcomes at 70%, 80% and 90% of the empirical outcome range. As recommended by Dul et al. (2023), effect sizes, scatterplots, ceilings and permutation results are interpreted together. "FDR-supported" identifies statistical evidence under the prespecified multiplicity rule and does not imply that case-deletion stability has been independently established.

3. Results

For hypothesis decisions, H1–H5 denote entrepreneurial experience (H1), family background (H2), related education/training (H3), agility/adaptability (H4), and technological complementarity (H5). The suffixes a, b and c denote process, product and technological innovation, respectively. Support is assessed using the Benjamini–Hochberg-adjusted results for the fifteen focal capability paths ($q < .05$); nominally significant results that do not meet this criterion are not counted as supported hypotheses.

3.1 Bootstrapped multiple regression

The process-innovation model explained 38.9% of the outcome variance ($R^2 = .389$; adjusted $R^2 = .372$). Agility/adaptability had the largest positive adjusted coefficient ($\beta = 0.561$, 95% bootstrap CI [.367, .759], FDR $q = .003$; $f^2 = .157$). Family background was also positively associated with process innovation ($\beta = 0.211$, CI [.058, .359], $q = .028$; $f^2 = .049$), supporting H4a and H2a. Technological complementarity had a negative conditional coefficient ($\beta = -.166$, CI [−.324, −.020]), but the association did not survive FDR correction ($q = .067$). This result does not establish that technology fit harms process innovation. A suppression mechanism cannot be established from the reported coefficients alone.

The product-innovation model explained 24.5% of the outcome variance ($R^2 = .245$; adjusted $R^2 = .224$). Technological complementarity was the only positive association retained after FDR correction ($\beta = 0.353$, CI [.190, .513], $q = .003$; $f^2 = .083$), supporting H5b. Agility/adaptability had a positive coefficient, but its 95% bootstrap interval included zero and its adjusted q-value exceeded .05 ($\beta = 0.196$, CI [−.004, .396], $q = .116$); H4b was therefore not supported. The absence of

other adjusted associations does not establish that these capabilities are unimportant, because their contributions may overlap with those of other predictors.

The technological-innovation model explained less outcome variance ($R^2 = .163$; adjusted $R^2 = .140$). Related education/training ($\beta = 0.229$, CI [.052, .399], $q = .049$) and technological complementarity ($\beta = 0.208$, CI [.042, .361], $q = .049$) showed positive associations, supporting H3c and H5c. Years of operation, included as a control in each model, was not statistically significant for all three outcomes. The two capability associations were close to the FDR significance threshold and should be interpreted cautiously.

Across the six regressors, VIFs ranged from 1.04 to 3.27. Breusch–Pagan tests indicated heteroskedasticity in the process-, product- and technological-innovation models ($p < .001$, $p = .0006$ and $p = .0013$, respectively), supporting the use of case-bootstrap intervals. The HC3 sensitivity checks retained the positive signs and conventional significance of the principal associations: agility/adaptability and family background with process innovation; technological complementarity with product innovation; and related education/training and technological complementarity with technological innovation. These checks concern inference rather than causation. **Table 3** presents all 15 focal bootstrap coefficients and confidence intervals.

Table 3. Bootstrapped standardized multiple-regression results

Hyp.	Relationship	β	95% bootstrap CI	p	q	f^2	Decision
H1a	Entrepreneurial experience → Process innovation	.106	[-.041, .255]	.156	.292	.011	Not supported
H2a	Family background → Process innovation	.211	[.058, .359]	.006	.028	.049	Supported
H3a	Related education/training → Process innovation	-.038	[-.219, .138]	.648	.693	.001	Not supported
H4a	Agility/adaptability → Process innovation	.561	[.367, .759]	< .001	.003	.157	Supported
H5a	Technological complementarity → Process innovation	-.166	[-.324, -.020]	.027	.067	.023	Not supported
H1b	Entrepreneurial experience → Product innovation	-.105	[-.262, .056]	.201	.335	.009	Not supported
H2b	Family background → Product innovation	-.046	[-.198, .102]	.552	.661	.002	Not supported
H3b	Related education/training → Product innovation	.036	[-.146, .214]	.693	.693	.001	Not supported
H4b	Agility/adaptability → Product innovation	.196	[-.004, .396]	.054	.116	.016	Not supported
H5b	Technological complementarity → Product innovation	.353	[.190, .513]	< .001	.003	.083	Supported
H1c	Entrepreneurial experience → Technological innovation	.071	[-.056, .202]	.285	.428	.004	Not supported
H2c	Family background → Technological innovation	-.054	[-.194, .088]	.462	.629	.002	Not supported
H3c	Related education/training → Technological innovation	.229	[.052, .399]	.016	.049	.027	Supported
H4c	Agility/adaptability → Technological innovation	.055	[-.134, .258]	.573	.661	.001	Not supported

Continued table:

Hyp.	Relationship	β	95% bootstrap CI	p	q	f^2	Decision
H5c	Technological complementarity → Technological innovation	.208	[.042, .361]	.014	.049	.026	Supported

Note. N = 227; β values are standardized OLS coefficients. The 95% intervals are case-bootstrap percentile intervals (5,000 resamples). Two-sided bootstrap sign-tail p-values include a plus-one correction; q-values are Benjamini–Hochberg adjustments across 15 focal capability paths. f^2 reflects predictor deletion. Years of operation is included in each regression but excluded from the FDR family. Values displayed as <.001 are not zero.

3.2 Necessary conditions and bottlenecks

NCA identified FDR-supported empirical ceilings for three process-innovation inputs: family background (d = .160, permutation q = .020), agility/adaptability (d = .120, q < .001) and technological complementarity (d = .164, q < .001). Entrepreneurial experience and related education/training had no CE-FDH empty zone for process innovation. All five capabilities had d = 0 for product innovation. Thus, the sample did not establish a single-capability bottleneck for product innovation: high outcome scores were observed at low levels of each candidate input.

For technological innovation, CE-FDH effects were .133 for entrepreneurial experience, .196 for agility/adaptability and .262 for technological complementarity. None survived correction across the 15 NCA tests (smallest adjusted q = .066). These results describe exploratory boundary patterns rather than established necessary conditions. Effect size alone does not justify a necessity claim, particularly with discrete survey scores and ceilings that may depend on individual observations.

At a process-innovation target of 80% of the observed outcome range, the CE-FDH ceilings corresponded to minimum observed scores of 1.6 for family background (20.0% of its range), 1.8 for agility/adaptability (26.7%) and 2.6 for technological complementarity (53.3%). Reaching these levels does not guarantee high process innovation. **Figure 2** shows the three ceiling patterns, and **Table 5** summarizes the bottlenecks at three target levels. See **Table 4**.

Table 4. CE-FDH necessary-condition results with permutation tests

Outcome	Condition	CE-FDH d	p	q	Interpretation
Process innovation	Entrepreneurial experience	0.000	1.000	1.000	No ceiling
Process innovation	Family background	.160	.004	.020	FDR-supported ceiling
Process innovation	Related education/training	0.000	1.000	1.000	No ceiling
Process innovation	Agility/adaptability	.120	< .001	< .001	FDR-supported ceiling
Process innovation	Technological complementarity	.164	< .001	< .001	FDR-supported ceiling
Product innovation	Entrepreneurial experience	0.000	1.000	1.000	No ceiling
Product innovation	Family background	0.000	1.000	1.000	No ceiling
Product innovation	Related education/training	0.000	1.000	1.000	No ceiling
Product innovation	Agility/adaptability	0.000	1.000	1.000	No ceiling
Product innovation	Technological complementarity	0.000	1.000	1.000	No ceiling
Technological innovation	Entrepreneurial experience	.133	.017	.066	Exploratory / not FDR-robust
Technological innovation	Family background	.133	.582	1.000	Exploratory / not FDR-robust
Technological innovation	Related education/training	.080	.071	.152	Exploratory / not FDR-robust
Technological innovation	Agility/adaptability	.196	.047	.116	Exploratory / not FDR-robust
Technological innovation	Technological complementarity	.262	.027	.082	Exploratory / not FDR-robust

Note. d is the empirical upper-left ceiling-zone proportion (0 indicates no observed restriction). Permutation p-values use 10,000 shuffles and a plus-one correction; q-values adjust 15 NCA tests by the Benjamini–Hochberg method. FDR support reflects adjusted permutation significance; the ceilings remain sample-specific, and individual-record deletion stability is not inferred from the permutation test alone.

Table 5. Observed CE-FDH bottlenecks for FDR-supported process-innovation conditions

Process innovation target	Family background	Agility/adaptability	Technological complementarity
70%	20.0% (score 1.6)	26.7% (score 1.8)	26.7% (score 1.8)
80%	20.0% (score 1.6)	26.7% (score 1.8)	53.3% (score 2.6)
90%	20.0% (score 1.6)	26.7% (score 1.8)	53.3% (score 2.6)

Note. Percentages indicate the minimum required share of the observed 1–4 input score range, not respondent percentages; scores are displayed in parentheses. Targets are percentages of the observed process-innovation range. These are sample-specific observed floors, not sufficient or causal intervention targets.

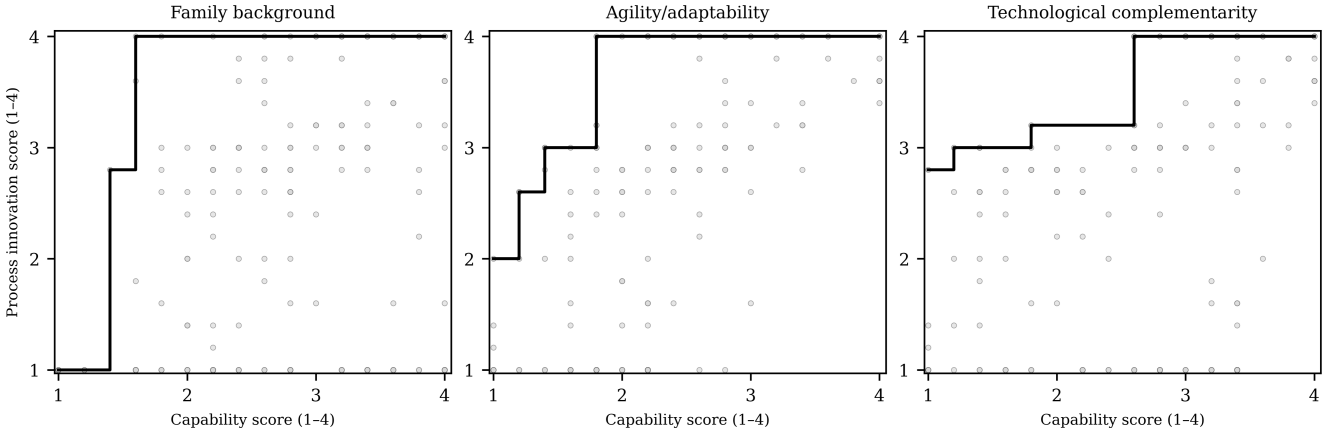

Figure 2. CE-FDH ceilings and individual observations for three process-innovation capability indices

3.3 Integrating regression and necessity evidence

The two analyses identify different capability roles. Family background and agility/adaptability are positive adjusted correlates of process innovation and exhibit FDR-supported, sample-specific NCA bottlenecks. Technological complementarity also exhibits a process-innovation ceiling, although its negative conditional regression coefficient does not survive FDR correction. For product innovation, technological complementarity is a positive correlate without a detected necessity ceiling. For technological innovation, related education/training and technological complementarity show positive adjusted associations, but no capability has an FDR-supported necessity result. **Table 6** summarizes these findings without assigning causal interpretations.

Table 6. Integrated interpretation of regression and NCA evidence

Outcome / resource	Regression result	NCA result	Interpretation
Process / family background	Positive, FDR-significant	FDR-supported ceiling	Positive correlate and empirical bottleneck
Process / agility	Positive, FDR-significant	FDR-supported ceiling	Strongest net correlate and empirical bottleneck
Process / technology fit	Not positive after FDR	FDR-supported ceiling	Potential enabling floor; no positive adjusted slope
Product / technology fit	Positive, FDR-significant	No ceiling	Positive correlate; no observed single-input minimum
Technological / related education	Positive, FDR-significant	Not FDR-robust	Small adjusted association; no confirmed floor
Technological / technology fit	Positive, FDR-significant	Not FDR-robust	Small adjusted association; no confirmed floor

4. Discussion

4.1 Reconsidering the capability–innovation relationship

The findings distinguish conditional average associations from empirical ceiling restrictions. Dynamic-capabilities research emphasizes knowledge and resource reconfiguration (Teece, 2007; Felin et al., 2012); the present analysis suggests that their observed roles vary across innovation outcomes. Family background and agility/adaptability were positively associated with process innovation, technological complementarity with product innovation, and related education/training and technological complementarity with technological innovation. This pattern supports examining capabilities separately, although self-reported cross-sectional data cannot establish the underlying organizational mechanisms.

The analysis extends the questions addressed in earlier bakery studies. Abellana, and Alonzo (2025a) examined innovation and distribution strategies; Abellana, and Alonzo (2025b) studied growth predictors in a smaller sample; and Abellana, et al. (2026) examined innovation and growth in the 227-case study population. The present study instead examines innovation as the outcome and combines regression with NCA to distinguish conditional associations from observed capability floors. Evidence about innovation and growth does not, by itself, identify which capabilities accompany particular forms of innovation.

The association between family background and process innovation is consistent with family-capital accounts of tacit routines, trust and knowledge transfer (Dyer et al., 2014). However, family background was not an FDR-significant adjusted correlate of product or technological innovation. Its role therefore appears specific to the outcome examined. The findings do not demonstrate that family-owned firms outperform other firms: the measure concerns family background, and the study does not compare validated ownership categories.

Technological complementarity illustrates the distinction between conditional average associations and necessity patterns. Its process-innovation coefficient was negative but did not survive FDR correction, whereas its bivariate NCA ceiling was FDR-supported. These analyses examine different features of the joint distribution and should not be treated as contradictory causal findings. The reported results do not establish a suppression mechanism or a minimum technology investment required for improvement. Future fieldwork could examine whether alignment among equipment, tools and work routines constrains process reorganization, including where other adaptive capabilities are present.

For product innovation, technological complementarity had a positive adjusted association without a detected single-condition ceiling. This finding does not establish that technology is unimportant; it indicates that high product-innovation scores occurred at low levels of each individual capability in the sample. Customer information, supplier collaboration and practical skills are plausible additional resources identified in food-innovation research (Avermaete et al., 2004). They warrant investigation but were not tested as substitutes in this dataset.

Related education/training and technological complementarity were positively associated with technological innovation after adjustment, whereas entrepreneurial experience was not. This pattern is consistent with the distinction between general human-capital proxies and task-related knowledge discussed by Unger et al. (2011). However, measurement limitations, the skewed outcome distribution and q-values close to .05 warrant caution. The absence of an FDR-supported NCA result also limits any claim that a minimum level of training is necessary.

4.2 Practical and policy implications

Capability support for bakery MSMEs could be tailored to the innovation outcome. For process improvement, assessment could focus on family-linked production knowledge, adaptive work routines and the fit between equipment and

existing operations. These indices were associated with high process-innovation responses or empirical ceilings in this sample; they were not tested intervention thresholds. Prospective studies could compare training, structured problem-solving and equipment integration to establish which approaches improve outcomes. Research on manufacturing cycle times and workflow delays offers an operational context for such studies (Alonzo & Abellana, 2024).

For product innovation, the positive association with technological complementarity suggests a possible role for equipment and workflow compatibility. However, the absence of a detected single-capability ceiling does not support prescribing a universal technology threshold. The contributions of customer knowledge, supplier relationships and practical production skills should be evaluated alongside technology fit.

For technological innovation, applied training and equipment–process compatibility warrant further evaluation, given their positive adjusted associations and small effect sizes. Potential intervention areas include technician training, equipment diagnostics, digital-order processing and team cross-training. These are proposals for future research, not estimated programme effects. The discussion is consistent with regional reports of underinvestment in human capital (Alonzo et al., 2025) and the relevance of organizational readiness to agribusiness digital adoption (Alonzo & Abellana, 2025).

4.3 Limitations and future research

The cross-sectional, nonprobability survey and self-reported measures limit causal interpretation and population-wide generalization. OLS summarizes conditional mean associations, whereas CE-FDH identifies sample-specific ceilings that may depend on upper-envelope observations and the finite 1–4 response scale (Dul et al., 2023). Bootstrap intervals and permutation tests with FDR adjustment address aspects of statistical inference, but do not establish causal intervention thresholds (Sorjonen & Melin, 2023).

All forty items were retained to preserve the original index definitions. The agility/adaptability coefficient ($\alpha = .615$) and the weak item–rest correlations for C25 and D11 indicate a need for measurement refinement, particularly where employee competencies or specific technology applications are of interest. The dissertation is cited as the source of instrument and consent materials, but its 113-case study remains distinct from the present 227-case secondary analysis.

Future research should examine item wording and dimensionality, assess the eight indices in other bakery populations and evaluate interventions longitudinally. Alternative ceiling estimators and prespecified necessity hypotheses could help assess the stability of the NCA patterns, while configurational methods could examine combinations of resources associated with product innovation. Prospective intervention studies are needed to establish whether developing a capability identified as an empirical bottleneck expands achievable innovation outcomes.

5. Conclusion

In this secondary analysis of 227 bakery MSMEs, capability roles differed across process, product and technological innovation. Agility/adaptability and family background were positive adjusted correlates of process innovation and exhibited FDR-supported empirical ceilings. Technological complementarity also exhibited a process-innovation bottleneck, although its conditional regression association did not survive FDR correction. Technological complementarity was positively associated with product innovation without a detected necessity ceiling. Related education/training and technological complementarity were positively associated with technological innovation, but no NCA test for that outcome survived FDR adjustment.

Combining bootstrapped multiple regression with CE-FDH NCA distinguishes

capabilities associated with higher average outcomes from those exhibiting observed minimum levels for high outcomes. The findings support examining capability development in relation to specific innovation tasks. Neither a regression coefficient nor an empirical ceiling establishes a universal cause or a validated minimum investment requirement.

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Ethics approval and informed consent: At the time of data collection, formal institutional ethics clearance was not required under the prevailing institutional procedures. Nevertheless, the study adhered to established ethical principles governing research involving human participants. Informed consent was obtained through written or electronic consent procedures prior to participation. Respondents were informed of the study's purpose, the voluntary nature of their participation, the confidentiality of their responses, and their right to withdraw. Personal identifiers were excluded from the analytical dataset, and participants were informed that anonymized and aggregated findings could be disseminated through academic publications and presentations.

Data availability statement: The dataset analyzed in this study is not publicly available to protect respondent confidentiality but is available from the corresponding author on reasonable request.

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