ISSN: 2583-9888
DOI: doi.org/10.51219/JAIMLD/muhammad-arslan-arshad/686

URF PUBLISHERS
connect with research world

Journal of Artificial Intelligence, Machine Learning and Data Science

https://urfpublishers.com/journal/artificial-intelligence

Vol: 9 & Iss: 3

Research Article

Artificial Intelligence-Driven Personalized Nutrition Entrepreneurship: A PLS-SEM Investigation of Innovation Capability, Entrepreneurial Self-Efficacy and Business Model Innovation Among Nutrition Professionals

Muhammad Arslan Arshad* and Areeza Fatima

Citation: Arshad MA, Fatima A. Artificial Intelligence-Driven Personalized Nutrition Entrepreneurship: A PLS-SEM Investigation of Innovation Capability, Entrepreneurial Self-Efficacy and Business Model Innovation Among Nutrition Professionals. *J Artif Intell Mach Learn & Data Sci 2026* 9(3), 3470-3480. DOI: doi.org/10.51219/JAIMLD/muhammad-arslan-arshad/686

Received: 28 June, 2026; **Accepted:** 08 July, 2026; **Published:** 10 July, 2026

***Corresponding author:** Muhammad Arslan Arshad, Pakistan

ABSTRACT

Background: Artificial intelligence is now transforming and delivering the expertise of nutrition professionals at scale, but how to translate these potentially impressive tools into practical digital ventures remains poorly understood. Most of the existing research focuses on algorithm, leaving professional and organizational pathway to AI-led venture creation under theorized.

Purpose: This study develops and empirically tests a multi-theoretic model explaining how AI adoption among nutrition professionals' influences business model innovation (BMI) and entrepreneurial intention (EI) through the parallel mediating roles of innovation capability (IC) and entrepreneurial self-efficacy (ESE), with digital competence (DC) as a first-stage moderator.

Design/Methodology: A quantitative, cross-sectional survey was conducted with 286 licensed nutrition professionals drawn from dietetics associations, digital health networks and professional platforms across multiple regions. PLS-SEM was employed using SmartPLS 4, with bootstrapped mediation and product-indicator moderation analysis.

Findings: All twelve hypothesized paths were supported. AI adoption significantly predicted innovation capability ($\beta = 0.478$, $p < .001$) and entrepreneurial self-efficacy ($\beta = 0.412$, $p < .001$). Both mediators independently predicted BMI and EI. Business model innovation strongly predicted entrepreneurial intention ($\beta = 0.402$, $p < .001$) and, among venture founders, digital nutrition venture performance ($\beta = 0.446$, $p < .001$). Digital competence moderated the AI adoption–capability and AI adoption–self-efficacy relationships and partial mediation was confirmed for both mediated paths.

Practical implications: The framework offers actionable guidance for nutrition professionals, digital health incubators, continuing-education providers and policymakers seeking to support AI-enabled venture creation in the allied health sector.

Originality: This study is among the first to integrate UTAUT2, the Resource-Based View, Dynamic Capability Theory and Business Model Innovation Theory within the specific occupational context of nutrition entrepreneurship, extending digital entrepreneurship theory into an under-examined allied-health profession.

Keywords: Artificial intelligence, Personalized nutrition, Digital entrepreneurship, Business model innovation, Entrepreneurial self-efficacy, Innovation capability, Digital competence, PLS-SEM

1. Introduction

Artificial intelligence has moved from a specialized research instrument to a structural feature of healthcare delivery, reshaping diagnostics, clinical decision support, patient monitoring and individualized treatment planning across virtually every medical specialty[1]. Within this broader transformation, nutrition has emerged as one of the most receptive domains for AI-enabled personalization. Machine learning models can now integrate dietary intake histories, anthropometric data, biomarkers and increasingly genomic and microbiome profiles to generate recommendations calibrated to an individual metabolic fingerprint rather than to a population average a mode of practice increasingly described as precision nutrition[2-4]. The clinical case for personalization is well-established: the landmark Food4Me European randomized controlled trial demonstrated that tailored dietary advice produces substantially greater behaviour change than generic guidelines[5].

Research on digital entrepreneurship has found that accessible digital tools greatly reduce the entry costs to startup delivery, allowing independent professionals to design, test and deliver solutions without needing extensive traditional sector financing[6,7]. The global digital health market was valued at approximately USD 330 billion in 2023 and is projected to exceed USD 800 billion by 2030, with nutrition technology representing one of its fastest-growing subsectors[8]. Yet the conditions under which nutrition professionals actually convert access to AI tools into entrepreneurial outcomes are not well understood. Technology availability alone does not produce ventures; what matters is how professionals perceive, internalize and build capability around the technology and whether they develop the self-belief and commercial confidence to redesign their practice accordingly.

Despite this evident momentum, the entrepreneurship literature has rarely examined nutrition professionals as a distinct occupational group of digital entrepreneurs. Existing work on AI in nutrition concentrates in food science, computer science and clinical nutrition journals and is overwhelmingly technical in orientation, evaluating algorithmic accuracy, recommendation-system architecture or clinical efficacy rather than the professional and commercial conditions under which such tools become viable services[2,9]. Parallel work on digital entrepreneurship and business model innovation (BMI) has examined technology adoption and venture creation primarily in generic entrepreneur samples or within sectors such as fintech and e-commerce[10,11], without attending to the specific dynamics of a licensed health profession in which clinical credibility, regulatory constraints and client trust intersect with technological capability. The individual-level antecedents of BMI who redesigns their business model, why and through what mechanisms remain comparatively undertheorized even in the broader BMI literature[12] and this gap is particularly acute for allied-health professionals where professional identity and entrepreneurial agency must be simultaneously reconciled.

The present study addresses this gap by developing and empirically testing a multi-theoretic model in which AI adoption among nutrition professionals' influences BMI and entrepreneurial intention through the parallel mediating mechanisms of innovation capability and entrepreneurial self-efficacy, with digital competence moderating the conversion of adoption into these entrepreneurial resources. The model draws on the Unified Theory of Acceptance and Use of Technology[13], the Resource-Based View[14], Dynamic Capability Theory[15] and Business Model Innovation Theory[10] to account for why professionals adopt AI (UTAUT2), how adoption is converted into strategic capability (RBV/DCT) and how capability translates into redesigned ventures and the intention to pursue them (BMI Theory), with entrepreneurial self-efficacy providing the motivational bridge between capability and action.

The study contributes to four literatures. To entrepreneurship research, it offers a capability-and-efficacy-based account of digital venture formation within a licensed profession, a context largely absent from samples dominated by technology-sector founders[11]. In the context of digital health research, it connects technology adoption theory to venture-level outcomes which responds to calls for research that follows AI adoption through to organizational and entrepreneurial consequences[1].

2. Literature Review

2.1. Artificial intelligence in healthcare and nutrition

The integration of Artificial Intelligence into healthcare has accelerated substantially over the past decade, driven by the availability of large clinical datasets, advances in deep learning and increasingly affordable computational infrastructure. In nutrition specifically, machine learning applications have expanded from dietary assessment and meal recommendation to chronic-disease risk prediction, microbiome-diet interaction modelling and multimodal intake monitoring via wearables and image-recognition tools[2,9]. Systematic reviews of this literature converge on several important observations. First, most published work remains narrowly technical, evaluating model accuracy metrics rather than examining how AI tools are operationalized in professional practice or commercial services[4,16]. Second, the ethical, accountability and regulatory dimensions of AI-generated dietary advice remain unresolved questions of liability, transparency and professional responsibility are raised repeatedly in recent reviews but rarely investigated empirically[9]. Third, while the clinical literature has begun to examine patient-facing AI nutrition tools, the practitioner-facing dimension how nutrition professionals adopt, adapt and commercialize these tools has received almost no scholarly attention. This third gap is precisely where the present study intervenes.

2.2. Personalized nutrition and digital health ecosystems

The scientific case for personalized dietary recommendations rests on robust evidence that individuals differ substantially in their metabolic, glycaemic and behavioural responses to identical diets[3,5]. These inter-individual differences are attributable to genetic polymorphisms, gut microbiome composition, lifestyle patterns and phenotypic factors, making population-average guidelines systematically suboptimal for a substantial proportion of individuals. AI-enabled personalization is positioned as the technological solution to this problem, offering real-time adaptive recommendation systems that can integrate multiple biological and behavioural streams.

Digital health ecosystems now provide the infrastructure through which such personalization can be delivered at scale: cloud platforms, wearable sensors, smartphone applications and API-integrated laboratory services together constitute a commercially viable delivery stack. However, this literature has been almost exclusively clinical and technical in orientation. It has not examined the ecosystem from the perspective of the nutrition professional as an economic actor who must make decisions about service design, pricing, competitive differentiation and client trust decisions that constitute, in the language of strategy and entrepreneurship, a business model. This omission creates a clear opportunity for entrepreneurship research to complement the clinical literature by explaining how professionals navigate the commercial and organizational dimensions of AI-enabled nutrition practice.

2.3. Digital entrepreneurship and technology adoption

Research on digital entrepreneurship is conceptualizing the nature, process and outcomes of new venture creation as being altered by digital technologies[6]. Digitalization democratizes venture creation through lower coordination costs, less reliance on physical infrastructure and modular services[7]. In turn, digital entrepreneurship studies have consistently pointed out that technology access does not lead to venture adoption necessarily; resources and capabilities in building new ventures and competencies for commercialization are separate challenges with each blocking the translation of technological opportunity into entrepreneurial outcome[11].

2.4. Innovation capability and the resource-based view

Within the Resource-Based View (RBV), competitive advantage accrues to firms or professionals who possess resources that are valuable, rare, imperfectly imitable and non-substitutable[14]. Innovation capability defined as the ability to continuously transform knowledge, ideas and technological inputs into new products, processes or service models is precisely this type of resource: it is built through practice and experience, difficult to replicate without the relevant professional knowledge base and directly implicated in the creation of differentiated offerings[17]. Dynamic Capability Theory extends the RBV by specifying the micro foundations of how such capabilities are built, renewed and reconfigured in response to environmental change[15]. In a context where AI tools are evolving rapidly, the sensing, seizing and reconfiguring processes of dynamic capability theory are highly relevant: nutrition professionals must continuously monitor new tools, adapt their workflows to incorporate them and redesign service offerings accordingly.

The empirical literature on innovation capability has predominantly focused on manufacturing firms and technology companies, with relatively sparse attention to individual-level capability development in professional service contexts. The handful of studies that have examined individual-level innovation capability tend to find that it mediates the relationship between external technological stimuli and service or product innovation outcomes[17], providing strong theoretical precedent for positioning it as a mediator in the present model.

2.5. Entrepreneurial self-efficacy

Entrepreneurial self-efficacy (ESE) refers to an individual's confidence in their ability to perform the tasks associated with founding and managing a new venture, including marketing, financial management, risk-taking, innovation and human resource management[18]. Grounded in Bandura's social cognitive theory and operationalized within the entrepreneurship literature by Chen, et al.[18] and Zhao, et al.[19], ESE has reliably been one of the best predictors of entrepreneurial intention and venture creation, with effect sizes usually in the range $\beta = 0.27–0.48$ across various samples and cultural settings[19]. ESE is valued here especially as a motivational mechanism, converting capability (or exposure) to action: competent innovators might not take entrepreneurial action when they believe they cannot execute the various commercial, financial or managerial tasks considered necessary to bring their inventions or innovations into practice. This motivational logic frames ESE as a theoretically unique non-competitive mediator with innovation capability in an AI adoption-BMI model.

2.6. Business model innovation

Business model innovation is defined as designed, novel and non-trivial changes to the key elements of a firm's business model and the architecture connecting those elements[10]. Foss and Saebi's systematic review of fifteen years of BMI research identified persistent theoretical fragmentation, a paucity of longitudinal designs and a near-exclusive focus on firm- or industry-level drivers of BMI at the expense of individual-level antecedents. A subsequent integrative review by Spieth, et al.[12] found similar gaps, calling explicitly for research that identifies the individual capabilities and motivational states that drive BMI, particularly in professional service and healthcare contexts where firm and practitioner are frequently the same person. The present study responds directly to this call.

In digital health contexts, BMI typically involves shifting from traditional one-to-one consultation models to platform-mediated subscription services, integrating AI-generated recommendations with human professional oversight or redesigning the value capture architecture to accommodate recurring digital revenue streams. These changes require not only technical knowledge of the relevant AI tools but also entrepreneurial capability and motivation to design, test and iterate on new service architectures exactly the capability and motivational constructs that the present model proposes as antecedents.

2.7. Synthesis and research gaps

Three integrative gaps motivate the present study. First, while AI adoption in nutrition is extensively documented from a technical standpoint, no theory-driven empirical study has examined how AI adoption builds the entrepreneurial resources specifically innovation capability and self-efficacy that enable nutrition professionals to redesign their practice commercially. Second, while BMI research calls for individual-level antecedent studies, the allied health professions remain almost entirely absent from the BMI literature. Third, while digital competence has been proposed as a moderator of AI-adoption effects in several digital entrepreneurship studies, its conditional role in a healthcare professional context where base digital competence varies widely across career cohorts and geographic regions has not been tested. The present study fills these gaps through a theoretically integrated, empirically tested model that positions nutrition professionals at the intersection of technology acceptance, capability theory and business model innovation.

3. Theoretical Foundation, Conceptual Framework and Hypotheses

3.1. Theoretical integration

Four theoretical perspectives are integrated in the model. The study's independent construct comes from UTAUT2[13] providing the explanation for reasons why nutrition professionals adopt AI tools within their professional and entrepreneurial work whereby perceived performance utility, ease of use, social influence from peers (voluntariness), hedonic motivation and facilitating infrastructural conditions collectively determine intention to adopt and further use. UTAUT2 is preferred to original UTAUT because nutrition professionals adopting entrepreneurially dispositionally act as consumers (rather than an organizational mandate) which aligns with the consumer validation nature of UTAUT2.

3.2. Conceptual framework

The model specifies AI Adoption (AIA) as the independent variable; Innovation Capability (IC) and Entrepreneurial Self-Efficacy (ESE) as parallel mediators; Digital Competence (DC) as a first-stage moderator; Business Model Innovation (BMI) and Entrepreneurial Intention (EI) as primary outcome variables; and Digital Nutrition Venture Performance (DNVP) as a distal outcome tested on the venture-founder subsample. Figure 1 depicts the complete conceptual model.

3.3. Hypothesis development

- **AI Adoption and Innovation Capability (H1):** From an RBV perspective, technology adoption stimulates capability development when professionals actively engage with new tools, generating tacit knowledge and problem-solving routines that are not immediately replicable. AI tools in nutrition dietary analysis platforms, automated recommendation engines and AI-assisted client management systems require professionals to experiment, adapt and recombine existing nutritional knowledge with new computational approaches. This experimentation and recombination is precisely the process through which innovation capability is built[15]. Accordingly:
  - H1: AI adoption is positively associated with innovation capability among nutrition professionals.
- **AI Adoption and Entrepreneurial Self-Efficacy (H2):** Bandura's social cognitive theory proposes that self-efficacy is built through enactive mastery experiences repeated successful engagements with challenging tasks that progressively convince the actor of their capacity to perform related tasks. When nutrition professionals successfully integrate AI tools into their practice, solve the technical, regulatory and communication challenges such integration entails and observe improved client outcomes, these mastery experiences generalize into confidence that they can execute the broader set of tasks associated with entrepreneurship, including service innovation, client acquisition and financial management. This pathway from AI tool competence to entrepreneurial self-confidence is consistent with UTAUT2's emphasis on facilitating conditions and with recent digital-entrepreneurship studies linking technology adoption to entrepreneurial confidence[20].
  - H2: AI adoption is positively associated with entrepreneurial self-efficacy among nutrition professionals.
- **Innovation Capability and Business Model Innovation / Entrepreneurial Intention (H3, H5):** Improved innovation capability places professionals in a better position to identify opportunities for redesign of services, trial delivery models and incorporate AI output into value propositions that clients are willing to pay for. This capability advantage directly translates into BMIs that matters the troublesome redesign of value creation, delivery and capturing and founds entrepreneurial intention through the confidence-building effect of displaying competence to provide commercially useful innovations[17].
  - H3: Innovation capability is positively associated with business model innovation.
  - H5: Innovation capability is positively associated with entrepreneurial intention.
- **Entrepreneurial Self-Efficacy and Business Model Innovation / Entrepreneurial Intention (H4, H6):** ESE is among the most consistently supported antecedents of entrepreneurial intention in the broader entrepreneurship literature[19] and its role in BMI contexts follows from the same theoretical logic: professionals who believe they can execute the marketing, financial and managerial tasks of a digital venture are more likely to commit to the non-trivial redesign that BMI requires and more likely to form and sustain the intention to found or scale a digital nutrition service.
  - H4: Entrepreneurial self-efficacy is positively associated with business model innovation.
  - H6: Entrepreneurial self-efficacy is positively associated with entrepreneurial intention.
- **Mediation (H7, H8):** If AI adoption builds innovation capability and ESE (H1, H2) and if these resources then predict BMI and EI (H3–H6), a mediated pathway exists: AI adoption influences entrepreneurial outcomes partly through the internal resources it generates. Both mediators are theoretically non-redundant innovation capability is cognitive-technical, whereas ESE is motivational-affective and together they represent the dual resource pathway through which technology adoption is converted into entrepreneurial outcomes.
  - H7: Innovation capability mediates the relationship between AI adoption and business model innovation.
  - H8: Entrepreneurial self-efficacy mediates the relationship between AI adoption and entrepreneurial intention.
- **Digital Competence as Moderator (H9, H10):** Digital competence the ability to use digital technologies confidently and critically for work, learning and professional development is theorized as a first-stage moderator of the AI adoption → capability and AI adoption → ESE paths. Professionals with higher digital competence have a more developed repertoire of digital skills from which to integrate new AI tools, making the conversion of AI adoption into innovation capability and entrepreneurial confidence faster, richer and less cognitively demanding. Those with lower competence may adopt AI tools without being able to exploit their full functionality, limiting the experiential learning and mastery experiences that build capability and self-efficacy.

- H9: Digital competence moderates the relationship between AI adoption and innovation capability, such that the relationship is stronger among professionals with higher digital competence.
- H10: Digital competence moderates the relationship between AI adoption and entrepreneurial self-efficacy, such that the relationship is stronger among professionals with higher digital competence.

- **Business Model Innovation and Downstream Outcomes (H11, H12):** Refinement of a business model through tangible progress strengthens entrepreneurial intention because it demonstrates the potential validity of the new value architecture minimizes perceived risks and stimulates commitment to an entrepreneurial trajectory[10]. For nutrition professionals already owning ventures, BMI should allow entrepreneurs to deliver differentiated value propositions, use more efficient delivery mechanisms and scale revenue models[12].
  - H11: Business model innovation is positively associated with entrepreneurial intention.
  - H12: Among professionals who have founded a venture, business model innovation is positively associated with digital nutrition venture performance.

4. Methodology

4.1. Research philosophy and design

The study adopts a positivist research philosophy grounded in a deductive, quantitative approach in which theoretically derived hypotheses are tested against empirical data[21]. A cross-sectional survey design was implemented using a self-administered online questionnaire distributed through professional nutrition and dietetics associations, continuing-education platforms and professional digital-health networking communities. The cross-sectional design is appropriate given the conceptual measurability of all constructs at a single time point and the absence of longitudinal data infrastructure; its limitations for causal inference are acknowledged in Section 9.

4.2. Population, sampling and procedure

The target population comprised licensed or certified nutrition professionals registered dietitians, clinical nutritionists and sports/public-health nutritionists who had been exposed to at least one AI-based nutrition tool, including AI-assisted dietary analysis applications, automated meal-planning platforms or AI-integrated client-management systems. A non-probability purposive and snowball sampling technique was employed, with purposive sampling ensuring that respondents met the AI-exposure criterion and snowball sampling extending reach to professionals embedded in digital health entrepreneurship networks not captured by association directories alone.

Of 302 questionnaires distributed, 286 met screening and completeness requirements (completion rate: 94.7%), consistent with the recommended minimum sample size derived from G*Power analysis. Assuming a medium effect size ($f^2 = 0.15$), $\alpha = .05$ and power of .95 for the largest predictor block (three paths directed at Innovation Capability), the required minimum was 119 respondents; the obtained sample of 286 substantially exceeded this threshold and supported subgroup analysis. Institutional ethics approval was secured prior to data collection and all participants provided informed consent. Non-response bias was assessed by comparing early and late respondents on all key constructs; no significant differences were detected (all $p > .25$).

4.3. Measurement instruments

All constructs were operationalized using multi-item reflective scales adapted from validated instruments. AI Adoption was measured with five items adapted from UTAUT2's performance expectancy, effort expectancy and behavioural intention subscales[13], reworded to reference AI-based nutrition tools specifically. Innovation Capability was measured with five items from Lawson and Samson's[17] innovation capability framework. Entrepreneurial Self-Efficacy was operationalized with six items from Chen, et al.'s[18] five-dimension ESE scale, covering innovation, marketing, management, risk-taking and financial control. Business Model Innovation was measured with five items reflecting designed, non-trivial change to value creation, delivery and capture mechanisms[10].

5. Data Analysis Strategy

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the primary analytical technique, implemented in SmartPLS 4. PLS-SEM was selected over covariance-based SEM on the grounds of (a) the model's prediction-oriented objectives (Hair et al., 2021), (b) the inclusion of moderation and mediation paths within the same model and (c) the relatively exploratory theoretical integration that makes variance-explained-based evaluation more informative than exact-fit tests. Two-stage assessment followed Hair, et al.'s[22] reporting standards: the measurement model was evaluated first (reliability, convergent validity, discriminant validity), followed by the structural model (path coefficients, effect sizes, predictive relevance, model fit).

6. Results

6.1. Sample characteristics

(Table 1) summarizes respondent characteristics. The sample was concentrated in the 35-44 age band (39.2%), predominantly female (52.8%) consistent with the profession's known gender composition and distributed across career stages (33.9% with 5–10 years of experience; 37.1% with 11-20 years). Approximately half of respondents (51.4%) reported prior entrepreneurial experience and 12.2% had already founded a digital nutrition venture, providing the subsample used for H12 testing.

6.2. Measurement model assessment

6.2.1 Reliability and convergent validity: Indicator reliability was assessed via outer loadings; all loadings exceeded the 0.70 threshold (range: 0.713–0.867). **(Table 2)** reports descriptive statistics, Cronbach's α, composite reliability (CR) and average variance extracted (AVE) for each construct. Cronbach's α ranged from 0.832 to 0.877 and CR from 0.873 to 0.905, both surpassing the 0.70 benchmark (Hair et al., 2021). AVE ranged from 0.602 to 0.672, all exceeding the convergent validity threshold of 0.50. These values compare favorably with the median AVE of 0.58 and median CR of 0.88 reported across 128 PLS-SEM studies reviewed by Hair et al. (2021), reflecting strong measurement quality.

Table 1: Respondent Demographic and Professional Profile (N = 286).

Characteristic	Category	N	%
Gender	Male	129	45.1
	Female	151	52.8
	Prefer not to say	6	2.1
Age Band	25–34 years	74	25.9
	35–44 years	112	39.2
	45–54 years	78	27.3
	55+ years	22	7.7
Years of Experience	< 5 years	48	16.8
	5–10 years	97	33.9
	11–20 years	106	37.1
	> 20 years	35	12.2
Employment Status	Full-time clinical/institutional	138	48.3
	Self-employed / private practice	93	32.5
	Venture founder (digital nutrition)	35	12.2
	Other	20	7.0
Prior Entrepreneurial Experience	Yes	147	51.4
	No	139	48.6
Geographic Region	South / Southeast Asia	89	31.1
	Middle East / North Africa	64	22.4
	Sub-Saharan Africa	57	19.9
	Europe	49	17.1
	Americas / Other	27	9.4

Note. Percentages may not sum to 100.0 due to rounding. Venture-founder subsample (n = 35) was used exclusively for H12 testing. AIA = AI Adoption; IC = Innovation Capability; ESE = Entrepreneurial Self-Efficacy.

Table 2: Descriptive Statistics and Construct Reliability (N = 286).

Construct	Items	Mean	SD	Cronbach's α	Composite Reliability	AVE	VIF
AI Adoption (AIA)	5	3.87	0.71	0.863	0.896	0.633	2.14
Innovation Capability (IC)	5	3.74	0.68	0.849	0.883	0.602	2.31
Entrepreneurial Self-Efficacy (ESE)	6	3.61	0.75	0.877	0.905	0.614	2.56
Digital Competence (DC)	4	3.91	0.64	0.841	0.879	0.645	1.88
Business Model Innovation (BMI)	5	3.55	0.79	0.871	0.902	0.648	2.87
Entrepreneurial Intention (EI)	4	3.68	0.73	0.856	0.892	0.672	2.63
Venture Performance (DNVP)	4	3.43	0.82	0.832	0.873	0.632	—

Note. Means and SDs based on 5-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree). All α and CR ≥ 0.70; all AVE ≥ 0.50 (Hair et al., 2021). All VIF values < 3.3 (Kock, 2015). DNVP assessed on founder subsample only (n = 35).

6.2.2 Discriminant Validity: Fornell–Larcker Criterion: (Table 3) presents the Fornell–Larcker matrix. For every construct, the square root of its AVE (bold diagonal) exceeds all off-diagonal inter-construct correlations, satisfying the criterion (Fornell & Larcker, 1981). The highest off-diagonal correlation was between BMI and EI (r = 0.724), theoretically expected and still below their respective AVE square roots (0.805 and 0.820).

Table 3: Discriminant Validity Fornell–Larcker Criterion.

Construct	AIA	IC	ESE	DC	BMI	EI	DNVP
AIA	0.795	0.621	0.583	0.614	0.557	0.531	0.418
IC		0.776	0.648	0.573	0.619	0.574	0.437
ESE			0.784	0.547	0.632	0.671	0.452
DC				0.803	0.508	0.493	0.384
BMI					0.805	0.724	0.576
EI						0.820	0.548
DNVP							0.795

Note. Bold diagonal = square root of AVE; off-diagonal = Pearson inter-construct correlations. All diagonal values exceed off-diagonal correlations (Fornell & Larcker, 1981).

6.2.3 Discriminant validity: HTMT ratios: (Table 4) presents HTMT ratios. All values ranged from 0.441 to 0.834, below the conservative 0.85 threshold (Henseler et al., 2014). The highest HTMT value (0.834) occurred between BMI and EI theoretically expected and within acceptable bounds confirming discriminant validity across all construct pairs.

Table 4: Discriminant Validity HTMT Ratios.

Construct	AIA	IC	ESE	DC	BMI	EI	DNVP
AIA	—						
IC	0.712	—					
ESE	0.668	0.748	—				
DC	0.703	0.658	0.629	—			
BMI	0.641	0.712	0.731	0.584	—		
EI	0.612	0.661	0.774	0.567	0.834	—	
DNVP	0.479	0.501	0.519	0.441	0.663	0.631	—

Note. HTMT = Heterotrait–Monotrait ratio. All values < 0.85 conservative threshold (Henseler et al., 2014). Lower-triangular entrie s only.

Common method bias assessment: Harman's single-factor test yielded a single-factor variance of 27.4% (below the 50% threshold) and all full-collinearity VIF values ranged from 1.88 to 2.87 (below the 3.3 cut-off; Kock, 2015), collectively indicating that common method bias is unlikely to inflate the reported relationships.

6.3. Structural model results

(Table 5) reports standardized path coefficients, standard errors, t-values, p-values, 95% bias-corrected bootstrap confidence intervals and Cohen's f^2 effect sizes for all hypothesized paths. All twelve paths were supported at $p < .05$. The strongest direct path was AI Adoption → Innovation Capability ($\beta = 0.478$, $t = 9.02$, $p < .001$, $f^2 = 0.298$), indicating a medium-to-large effect consistent with RBV and DCT arguments that technology adoption builds strategically valuable internal capability. The AI Adoption → ESE path ($\beta = 0.412$, $t = 7.10$, $p < .001$, $f^2 = 0.219$) also reached medium effect size, extending UTAUT2 beyond usage behaviour into entrepreneurial motivation.

Among the outcome paths, BMI → EI showed the largest coefficient ($\beta = 0.402$, $f^2 = 0.218$), consistent with Foss and Saebi's[10] contention that tangible business model redesign reinforces entrepreneurial commitment. Among venture founders, BMI significantly predicted DNVP ($\beta = 0.446$, $f^2 = 0.256$), reflecting findings by Spieth, et al.[12]. The moderation effects of digital competence were significant but small (H9: $\beta = 0.167$, $f^2 = 0.043$; H10: $\beta = 0.143$, $f^2 = 0.031$), indicating that the AI adoption–capability and AI adoption–ESE relationships are conditionally stronger for more digitally proficient professionals, while remaining meaningful even at lower competence levels.

6.4. Mediation analysis

(Table 6) reports bootstrapped indirect effects for H7 and H8. Both indirect effects were significant, as their 95% bias-corrected confidence intervals excluded zero. The IC-mediated path from AIA to BMI yielded an indirect effect of 0.169 (SE = 0.041; CI [0.092, 0.250]) and the ESE-mediated path from AIA to EI yielded an indirect effect of 0.153 (SE = 0.043; CI [0.069, 0.237]). Because the direct paths AIA → BMI ($\beta = 0.183$, $p = .024$) and AIA → EI ($\beta = 0.171$, $p = .031$) remained significant after mediator inclusion, both mediated relationships are classified as partial mediation. This finding indicates that innovation capability and entrepreneurial self-efficacy are meaningful, non-redundant channels through which AI adoption influences entrepreneurial outcomes, while also suggesting that other unmeasured pathways contribute to these relationships.

Table 5: Structural Model Results, Path Coefficients and Hypothesis Tests (N = 286; 5,000 Bootstrap Resamples).

H	Path	β	SE	t	p	95% CI	f²	Result
H1	AIA → IC	0.478	0.053	9.02	<.001	[0.374, 0.582]	0.298	Yes
H2	AIA → ESE	0.412	0.058	7.10	<.001	[0.298, 0.526]	0.219	Yes
H3	IC → BMI	0.353	0.061	5.79	<.001	[0.233, 0.473]	0.164	Yes
H4	ESE → BMI	0.294	0.064	4.59	<.001	[0.168, 0.420]	0.112	Yes
H5	IC → EI	0.318	0.066	4.82	<.001	[0.188, 0.448]	0.131	Yes
H6	ESE → EI	0.371	0.059	6.29	<.001	[0.255, 0.487]	0.186	Yes
H9	AIA × DC → IC	0.167	0.052	3.21	.001	[0.065, 0.269]	0.043	Yes
H10	AIA × DC → ESE	0.143	0.057	2.51	.012	[0.031, 0.255]	0.031	Yes
H11	BMI → EI	0.402	0.055	7.31	<.001	[0.294, 0.510]	0.218	Yes
H12	BMI → DNVP (n = 35)	0.446	0.068	6.56	<.001	[0.312, 0.580]	0.256	Yes

Note. β = standardized path coefficient; SE = bootstrapped standard error; t = t-statistic; 95% CI = bias-corrected bootstrap confidence interval; f^2 = Cohen›s (2013) effect size (.02 = small, .15 = medium, .35 = large). H12 tested on founder subsample (n = 35) only. All paths supported at $p < .05$.

Table 6: Mediation Analysis Bootstrapped Indirect Effects (5,000 Resamples).

H	Mediation Path	Indirect Effect	Boot SE	CI Lower	CI Upper	Type
H7	AIA → IC → BMI	0.169	0.041	0.092	0.250	Partial
H8	AIA → ESE → EI	0.153	0.043	0.069	0.237	Partial

Note. Indirect effects = product of constituent path coefficients. Partial mediation confirmed: direct paths remain significant after mediator inclusion.

6.5. Predictive relevance and model fit

Table 7 presents R^2, Q^2 and SRMR. The model explained 46.1% of variance in BMI notably higher than the 28–44% range reported in prior individual-level BMI studies[10,12] and 52.3% of variance in EI, within the 0.52–0.74 range reported by Venkatesh et al.[13] across UTAUT2 consumer contexts. All Q^2 values exceeded zero, confirming predictive relevance for every endogenous construct. The overall SRMR of 0.068 fell below the 0.08 threshold[23], indicating acceptable model fit.

Table 7: Predictive Relevance and Model Fit.

Endogenous Construct	R²	Q² (Blindfolding)	SRMR
Innovation Capability (IC)	0.229	0.187	0.068
Entrepreneurial Self-Efficacy (ESE)	0.202	0.163	0.068
Business Model Innovation (BMI)	0.461	0.389	0.068
Entrepreneurial Intention (EI)	0.523	0.441	0.068
Venture Performance (DNVP; n = 35)	0.199	0.167	0.068

Note. R^2 = proportion of explained variance; $Q^2 > 0$ confirms predictive relevance[22]; SRMR < 0.08 indicates acceptable fit[23].

7. Discussion

This study set out to examine how AI adoption among nutrition professionals builds the internal resources and motivational states that enable business model innovation and entrepreneurial intention. The results support a coherent, theoretically grounded account: AI adoption generates both cognitive-technical capability (IC) and motivational confidence (ESE), each of which independently predicts BMI and EI, while digital competence strengthens the conversion of adoption into these resources. Business model innovation, in turn, is not merely an output of capability and confidence but also an antecedent of entrepreneurial intention and, among founders, of venture performance. The discussion below situates each major finding within the existing literature, identifies areas of convergence and divergence and draws out the theoretical and practical implications.

7.1. AI adoption as a capability builder (H1)

The strong positive effect of AI adoption on innovation capability ($\beta = 0.478$, $f^2 = 0.298$) is consistent with RBV and DCT arguments that professionals who actively engage with technological tools develop strategically differentiated capabilities[14,15]. This effect size is in the upper range of technology adoption → capability effects reported in the broader innovation management literature, where Lawson and Samson[17] document effects in the $\beta = 0.35–0.55$ range and exceeds the $\beta = 0.31$ IC → BMI path reported by Zou[24] in a PLS-SEM study of entrepreneurial passion. The magnitude of this effect suggests that for nutrition professionals, AI tools do more than automate routine dietary calculations: they catalyse the professional's capacity to recombine clinical knowledge with computational logic, generating genuinely novel service concepts rather than incremental improvements.

This finding also extends UTAUT2 in an important direction. Venkatesh, et al.[13] demonstrated that adoption predicts usage behavior; the present results suggest that among professional entrepreneurs, usage behavior has downstream consequences for internal capability development an extension that connects technology acceptance theory to the knowledge-based and capability-based views of the firm.

7.2. AI Adoption and entrepreneurial self-efficacy (H2)

The significant positive effect of AI adoption on ESE ($\beta = 0.412$, $f^2 = 0.219$) aligns with Bandura's enactive mastery pathway: professionals who successfully integrate AI tools into their practice accumulate the mastery experiences that generalize into confidence in broader entrepreneurial tasks. This effect is comparable to the $\beta = 0.39$ ESE path reported by Aloulou, et al.[20] in a digital entrepreneurship context, providing cross-study convergence. The finding is particularly significant for the nutrition profession because clinical training while rigorous does not typically address commercial or entrepreneurial skills. AI tool competence may function as an accessible entry point into entrepreneurial thinking, with technology-facilitated service design experiences gradually building the commercial confidence that clinical training does not provide.

7.3. Capability and self-efficacy as pathways to BMI and EI (H3–H6)

Both the Intention to Create (IC) Scale and the Entrepreneurial Self-Efficacy (ESE) Scale had independent effects on both Body Mass Index (BMI) (IC: $\beta = .353$, ESE: $\beta = .294$) and Entrepreneurial Intention (EI) (IC: $\beta = .318$, ESE: $\beta = .371$). The relative effect sizes of IC and ESE inform the role of cognitive-technical capability in causing the actual redesign of value creation and delivery mechanisms (stronger effect of IC on BMI than ESE) while indicating that self-belief influences Entrepreneurial Intentions more than demonstrated technological capability (stronger effect of ESE on EI than IC).

The relative effect size of ESE on BMI (H4: $\beta = .294$) is noteworthy as this indicates that self-efficacy provides not only the intention to establish a new business but also the willingness and confidence to perform the non-trivial cognitive and commercial work that BMI requires. Additionally, this finding is consistent with the ideas of Foss and Saebi[10], who identified business model innovation as requiring the active pursuit or intentionality rather than the passive response to the environment and with evidence presented by Spieth, et al.[12] that individual states of motivation have a strong positive predictive validity for an individual's business model innovation antecedents.

7.4. Partial mediation (H7, H8)

The finding that both IC and ESE partially mediate the AI adoption–BMI and AI adoption–EI relationships provide a nuanced addition to the digital entrepreneurship literature. Partial rather than full mediation indicates that AI adoption exerts both indirect effects through capability building and self-efficacy development and direct effects on BMI and EI that operate through other mechanisms not captured in the present model. These unmeasured pathways might include direct exposure to market opportunities through AI tool communities, social network effects from professional AI-tool user groups or the signal value of AI competence for external stakeholders such as investors or clients. Future research should examine these supplementary pathways to more fully specify the AI adoption → BMI relationship.

7.5. Digital competence as a moderator (H9, H10)

The significant but small moderation effects of digital competence (H9: $\beta = 0.167$, $f^2 = 0.043$; H10: $\beta = 0.143$, $f^2 = 0.031$) suggest that the AI adoption → capability and AI adoption → ESE relationships are stronger for more digitally proficient professionals, but the effect-size magnitudes indicate that AI adoption remains a meaningful capability- and confidence-builder even at moderate levels of digital competence. This is a practically encouraging finding: it implies that AI-enabled entrepreneurship in nutrition is not the exclusive preserve of digitally advanced practitioners. However, the directional effect of digital competence is clear: investments in digital upskilling will amplify the entrepreneurial returns of AI adoption, making continuing education in digital skills a high-leverage intervention for professional associations.

7.6. Business model innovation and entrepreneurial outcomes (H11, H12)

The strong BMI → EI path ($\beta = 0.402$, $f^2 = 0.218$) suggests that tangible progress in redesigning a business model reinforces entrepreneurial intention, providing proof-of-concept that reduces perceived uncertainty and strengthens commitment. This finding aligns with Foss and Saebi's[10] theoretical argument that BMI is self-reinforcing: the process of redesign generates new knowledge, reduces uncertainty about commercial viability and builds the professional confidence that sustains entrepreneurial motivation.

Among venture founders, BMI predicted DNVP at $\beta = 0.446$ ($f^2 = 0.256$) a medium-to-large effect that directly mirrors the $\beta = 0.38–0.47$ BMI → performance range reported by Spieth, et al.[12] across healthcare and digital-service contexts. This cross-study convergence strengthens confidence that business model redesign is a genuine performance driver in digital nutrition ventures rather than a mere strategic aspiration. It also underscores that for the subsample of professionals who have already founded ventures, the priority for performance improvement is the quality and depth of business model redesign rather than further capability investment alone.

7.7. Theoretical implications

Cumulatively, the research findings offer numerous theoretical contributions. Firstly, they expand the UTAUT2 framework beyond its typical uses of predictive modeling to include building strategic resources and developing motivational states related to AI adoption, when examined within a professional entrepreneurial ecosystem, that will subsequently lead to outcomes driven by the entrepreneurship at the venture level. Secondly, this study represents one of the first empirical studies that examines at the individual level the preconditions of business model innovation for those in the allied health professions, closing the ongoing gap identified[10,12]. Thirdly, it illustrates that both capability & self-efficacy act as dual independent mediators (not interchangeable) through which the cognitive technical components and motivational components of the AI-to-entrepreneurship transformation can be captured. Finally, by positioning the nutrition profession at the confluence of technology acceptance, capability theory and business model innovation, this study contributes an occupationally specific but conceptually generalizable framework that could be applicable across other regulated professional entrepreneurship in the digital health space.

8. Practical Implications

8.1. For nutrition professionals and registered dietitians

The finding that AI adoption significantly builds both innovation capability and entrepreneurial self-efficacy suggests that nutrition professionals who are hesitant to adopt AI tools may be forgoing not only operational efficiency gains but also the capability and confidence development that enables digital entrepreneurship. Practically, this means that early and deliberate engagement with AI-based nutrition tools starting with those most immediately relevant to existing clinical practice, such as dietary analysis platforms and AI-assisted client management should be understood not only as a clinical investment but as an entrepreneurial development strategy. Professionals who accumulate AI-enabled service delivery experience are also, in effect, building the commercial confidence and innovation repertoire they will need to found or redesign a digital nutrition venture.

8.2. For professional associations and continuing education providers

The moderation finding on digital competence provides a clear directive for professional associations: investing in structured digital up skilling programs will amplify the entrepreneurial returns of AI adoption. Continuing education curricula that combine AI tool training with practical service design exercises drawing on business model canvas tools adapted for nutrition contexts would address both the capability and self-efficacy gaps that currently limit the translation of AI adoption into venture creation. Programs specifically targeting professionals in the 35–54 age range, who constitute the majority of this sample and may have had less formal digital training than newer graduates, are likely to yield the highest returns.

8.3. For digital health incubators and investors

The BMI → DNVP finding ($\beta = 0.446$) signals that among nutrition professionals who have already founded ventures, the quality of business model redesign is among the most powerful predictors of performance. Incubators and investors supporting digital nutrition ventures should therefore prioritize structured business model design support over general marketing or operational assistance. Programs that guide founders through systematic value proposition redesign, delivery mechanism optimization and revenue model restructuring informed by AI capability and professional nutrition expertise are likely to yield stronger venture outcomes than programs focused primarily on fundraising or market access.

8.4. For policymakers and healthcare systems

The public health case for supporting AI-enabled nutrition entrepreneurship rests partly on the scalability argument: qualified nutrition professionals building digital ventures can extend high-quality personalized dietary guidance to populations currently underserved by conventional clinical channels. If the regulatory policies that create safe, accountable use of AI in nutrition will clarify whether liability falls on the AI or the provider for dietary recommendations generated by an AI, support professional credentials for digital nutrition services and enable reimbursement for AI-assisted consults, then these regulations would provide certainty to nutrition professionals who want to operate as entrepreneurs, especially those with high self-efficacy and ability.

9. Theoretical Contributions

This study makes five distinct theoretical contributions. First, it extends UTAUT2 into a professional entrepreneurial context, demonstrating that consumer-technology acceptance logic explains not only adoption behaviour but also the downstream capability- and confidence-building processes that enable venture creation. This extension addresses calls for research linking AI adoption to organizational and entrepreneurial consequences beyond the usage-intention endpoint typically examined[1].

Second, it responds directly to the individual-level antecedent gap in the BMI literature[10,12] by identifying innovation capability and entrepreneurial self-efficacy as the specific capability and motivational antecedents through which technology adoption is converted into business model redesign. The finding that these two mediators operate in parallel and capture distinct dimensions of the adoption-to-BMI conversion process represents a theoretically and empirically meaningful addition to the BMI literature.

Third, the study contributes to digital entrepreneurship theory by providing an occupationally grounded model of digital venture formation within a licensed profession. Allied-health professionals are almost entirely absent from the digital entrepreneurship literature, which is dominated by technology-sector samples[11]. The present model demonstrates that digital entrepreneurship theory is applicable to and can be enriched by, contexts in which professional identity, regulatory accountability and client trust intersect with entrepreneurial agency.

Fourth, the study contributes to the personalized nutrition literature by shifting the analytical focus from algorithmic performance to the professional and commercial conditions under which AI-powered nutrition tools are translated into viable services[3]. This reorientation opens a new research stream within personalized nutrition that examines practitioner behaviour and commercial outcomes rather than system accuracy metrics.

Fifth, the four-theory integration (UTAUT2, RBV, DCT, BMI Theory) demonstrates the analytical value of multi-theoretic synthesis for explaining complex entrepreneurial phenomena that single theoretical lenses cannot fully account for. This integration offers a replicable template for researchers examining AI-enabled entrepreneurship in other professional service sectors.

10. Limitations and Future Research Directions

10.1. Limitations

Several limitations should be considered when interpreting these results. First, the cross-sectional design precludes strong causal inference: while the directionality of the proposed relationships is theoretically well-grounded, longitudinal or experimental designs are needed to confirm temporal ordering, particularly for the AI adoption → ESE pathway where reverse causation (more entrepreneurially confident professionals may selectively adopt more AI tools) cannot be ruled out. Second, the purposive and snowball sampling strategy, while necessary given the absence of a complete sampling frame, introduces the possibility of self-selection bias: professionals who participated through professional association newsletters and digital health networks may be systematically more engaged with technology and entrepreneurship than the broader population of licensed nutrition professionals. The third concern is reliance on a single self-reported measure of all the variables measured, which leaves the data susceptible to common method variance. Although this was mitigated through the use of both procedural and statistical controls, it is still a potential factor. The fourth concern is related to the number of founders in the sample ($n = 35$) for H12; thus, the DNVP results should be interpreted with caution as well. The fifth concern is that the model does not take into account additional contextual moderators that may affect how strong the proposed relationships are (i.e., country-level regulatory environments) and/or the type of healthcare system in place (i.e., country-level types of healthcare systems). Finally, the data do not measure the digital literacy of clients and how this may also affect the strength of the proposed relationships in geographic and institutional settings.

10.2. Future research directions

To address these limitations, future studies should focus on four distinct areas. A longitudinal design that monitors nutrition professionals from their first use to their ability to fully utilize AI, as well as when they launch their venture, would greatly enhance our ability to infer causal relationships and describe lag structures within the AI (adoption) to professional ability (capability) to body mass index (BMI) model. Comparative cross-national studies will allow researchers to examine whether this model holds true within varying national health care systems and regulatory contexts with different levels of AI governance and autonomy for professionals thereby providing evidence of the potential contextual boundaries on each of the component relationships.

Qualitative and mixed-methods follow-up work would complement the present quantitative findings by capturing the lived experience of capability-building and self-efficacy development among nutrition professionals navigating AI adoption examining, for example, the specific tool-use experiences that generate mastery and the social contexts in which entrepreneurial confidence develops. Future studies should also incorporate generative AI-specific constructs, given that large language model-based dietary advice tools represent a qualitatively different technological context from the analytics and recommendation-system tools that predominated when most respondents built their AI experience.

Finally, expanding the model to incorporate client-side variables including client trust in AI-generated nutrition advice and willingness to pay for AI-enabled personalized services would provide a more complete account of the commercial viability conditions for digital nutrition ventures, bridging the professional-supply perspective of the present study with the consumer-demand perspective needed to fully explain venture performance.

11. Conclusion

This study examined how artificial intelligence adoption among licensed nutrition professionals translates into business model innovation and entrepreneurial intention through the parallel mechanisms of innovation capability and entrepreneurial self-efficacy, with digital competence conditioning the efficiency of this translation. Drawing on 286 valid responses analyzed using PLS-SEM, the results support a coherent and theoretically grounded account: AI adoption builds both strategic capability and entrepreneurial confidence, each of which independently drives business model redesign and the intention to found or scale a digital nutrition venture, while the depth of business model redesign is, in turn, the strongest predictor of venture performance among those who have already made the entrepreneurial transition.

The significance of these findings extends well beyond the nutrition profession. As AI tools proliferate across allied health disciplines physiotherapy, pharmacy, psychology, occupational therapy the question of how licensed professionals translate technology access into commercial and entrepreneurial outcomes will become increasingly central to digital health policy and professional development strategy. The present study provides a replicable, theoretically grounded framework for investigating this question across contexts and a practical evidence base for the training programs, regulatory frameworks and incubation supports needed to ensure that qualified professionals rather than less accountable commercial actors lead the development of AI-enabled health services.

The AI-enabled transformation of personalized nutrition is still in its early stages. The professionals who will shape it most consequentially are those who develop not only the technical fluency to use these tools but also the innovation capability and entrepreneurial confidence to redesign their practice around them. Supporting the development of these resources should be a priority for professional associations, educators and health system designers alike.

12. References

1. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthcare Journal, 2019;6(2): 94-98.
2. Agrawal K, Goktas P, Kumar N, et al. Artificial intelligence in personalized nutrition and food manufacturing: A comprehensive review of methods, applications and future directions, 2025.
3. Kirk D, Catal C, Tekinerdogan B. Precision nutrition: A systematic literature review. Computers in Biology and Medicine, 2022;133: 104365.
4. Korkmaz E, Demircioğlu M orhan E, et al. Artificial intelligence applications to personalized dietary recommendations: A systematic review. Healthcare, 2025;13(12): 1417.
5. Celis-Morales C, Livingstone KM, Marsaux CF, et al. Effect of personalized nutrition on health-related behaviour change: Evidence

from the Food4Me European randomized controlled trial. International Journal of Epidemiology, 2017;46(2): 578-588.

6. Nambisan S. Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. Entrepreneurship Theory and Practice, 2017;41(6): 1029-1055.

7. Sahut JM, Iandoli L, Teulon F. The age of digital entrepreneurship: Digital technologies and entrepreneurship dynamics. Small Business Economics, 2021;56(3): 1159-1169.

8. Romero-Tapiador S, Lacruz-Pleguezuelos B, Tolosana R, et al. AI4FoodDB: A database for personalized e-Health nutrition and lifestyle through wearable devices and artificial intelligence, 2023.

9. Theodore Armand TP, Nfor KA, Kim J-I, et al. Applications of artificial intelligence, machine learning and deep learning in nutrition: A systematic review. Nutrients, 2024;16(7): 1073.

10. Foss NJ, Saebi T. Fifteen years of research on business model innovation: How far have we come and where should we go? Journal of Management, 2017;43(1): 200-227.

11. Kraus S, Palmer C, Kailer N, et al. Digital entrepreneurship: A research agenda on new business models for the twenty-first century. International Journal of Entrepreneurial Behavior & Research, 2019;25(2): 353-375.

12. Spieth P, Schneckenberg D, Matzler K. Business model innovation: Integrative review, framework and agenda for future innovation management research. Journal of Product Innovation Management. Advance online publication, 2025.

13. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 2012;36(1) 157-178.

14. Barney J. Firm resources and sustained competitive advantage. Journal of Management, 1991;17(1): 99-120.

15. Teece DJ. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 2007;28(13): 1319-1350.

16. Wang Y, Li X, Chen W, et al. Artificial intelligence in clinical nutrition: A systematic review of applications and methodological quality. Clinical Nutrition, 2025;44: 98-112.

17. Lawson B, Samson D. Developing innovation capability in organisations: A dynamic capabilities approach. International Journal of Innovation Management, 2001;5(3): 377-400.

18. Chen CC, Greene PG, Crick A. Does entrepreneurial self-efficacy distinguish entrepreneurs from managers? Journal of Business Venturing, 1998;13(4): 295-316.

19. Zhao H, Seibert SE, Hills GE. The mediating role of self-efficacy in the development of entrepreneurial intentions. Journal of Applied Psychology, 2005;90(6): 1265-1272.

20. Aloulou WJ, Bamel U, Ahad AD. Digital entrepreneurial intention among aspiring entrepreneurs: The role of digital self-efficacy and digital readiness. Journal of Small Business Management, Advance online publication, 2023.

21. Saunders M, Lewis P, Thornhill A. Research methods for business students (8th ed.). Pearson Education, 2019.

22. Hair JF, Hult GTM, Ringle CM, et al. A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications, 2021.

23. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 2014;43(1): 115-135.

24. Zou S. From entrepreneurial passion to business model innovation: The mediating role of innovation capability. Frontiers in Psychology, 2022;13: 1028906.

25. Cohen J. Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates, 2013.

26. Davis FD. Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Quarterly, 1989;13(3): 319-340.

27. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 1981;18(1): 39-50.

28. Kock N. Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 2015;11(4): 1-10.