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Research paper

Unlocking Digital Success: A TOE Framework Analysis of Digital Marketing Adoption for Enhanced SMEs Competitiveness

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Abstract

This study analyzes the extent to which Technology-Organization-Environment (TOE) factors contribute to the adoption of electronic marketing and resulting business performance among small and medium-sized enterprises (SMEs) in Mimika, Indonesia. A quantitative, cross-sectional survey design collected data from 218 SMEs using validated tools and applying Partial Least Squares Structural Equation Modeling (PLS-SEM) and bootstrapping methods for analytical assessment. The findings suggest that technological forces have the largest positive effect on electronic marketing adoption ($\beta = 0.573$, $p < 0.001$), followed by organizational forces ($\beta = 0.232$, $p < 0.001$), and environmental forces ($\beta = 0.185$, $p < 0.005$). The adoption of electronic marketing is further seen to positively affect business performance ($\beta = 0.841$, $p < 0.001$). The structural model explains 83.6% of the variance for electronic marketing adoption and 70.7% of the variance for business performance. Despite limitations inherent to the cross-sectional design when it comes to causal implications and geographical limitations applied to generalizability, this research provides the first empirical validation of the TOE framework within the specific context of Indonesian SMEs adopting electronic marketing. The findings are reflective of a technology-led adoption model different from an organizational-led fashion common to more developed countries. The findings indicate that SMEs would be best advised to place importance upon determining their technology-readiness and examining platform compatibility, complemented by developing organizational capacity, to ensure enhanced capability to drive digital transformation, and hence make valuable contributory inputs to context-specific literature for emerging economies where technology-focused factors have a preponderant role to play when choosing an adoption model.

***Keywords**: Digital marketing adoption, TOE framework, SMEs competitiveness, Business performance, Emerging economies, Indonesia*

1. Introduction

The recent accelerated growth of digital technologies has significantly reshaped the competitive forces governing global markets, bringing unprecedented potential and significant challenges to Small and Medium-sized Enterprises (SMEs) worldwide (Maghyereh & Abdoh, 2021; R. Zhao et al., 2023). Although these technologies hold out hope of improved efficiency of operations, greater market access, and enhanced customer interaction options, findings of empirical research indicate important variations in adoption levels and ensuing implications across different economic settings (Nambisan et al., 2019). Such differences are especially prominent when comparing developed and emerging market settings, where SMEs are faced by very different resource constraints, infrastructural issues, and institutional constraints, which importantly shape not just technology adoption processes but the resulting implications (Kamolsareeratana & Kouwenberg, 2023; Satyro et al., 2024; Taherdoost et al., 2024). Despite the critical need to understand such contextual differences, extant technology adoption literature pays little specific attention to conditions within developed economies, thus bringing about significant theoretical and pragmatic knowledge deficiencies concerning processes of digitalization within emerging markets (Christofi et al., 2024; Hadjielias et al., 2022)

Digital marketing technologies represent an important area for increasing the competitive advantage of small and medium-sized enterprises (SMEs), enabling resource-constrained organizations to offset traditional disadvantages through affordable customer contact, greater product and service visibility, and data-driven choice (El-Rayes et al., 2023; Nadányiová et al., 2021). However, adoption of digital marketing technologies involves multifaceted interactions between technological attributes, organizational capacity, and contextual factors, going beyond simple cost-benefit rationality (Venkatesh, 2008; Venkatesh & Morris, 2000). The Technology-Organization-Environment (TOE) framework proposed by Tornatzky (1992)provides an integrative theoretical view of understanding these multifaceted adoption processes, especially how technological readiness, organizational ability, and external conditions jointly influence innovation adoption choice (Edvardsson & Durst, 2022; Kraus et al., 2022). Even though considerable empirical support has been demonstrated for the TOE model across a wide range of technological domains and organizational contexts, application to SMEs adopting digital marketing technologies within emerging markets has been relatively limited, thereby limiting theoretical and pragmatic implications for policy and managerial choice within these critical economic spaces (Athaide et al., 2024; Pascucci et al., 2023).

A thorough examination of existing literature highlights three theoretical and empirical limitations that hinder an integrative understanding of the adoption of electronic marketing in emerging markets (Melović et al., 2020; Yang et al., 2022). First, most research applying the Technology-Organization-Environment (TOE) framework has been tested in developed economies, which are marked by rich digital infrastructure, complex institutional arrangements, and high levels of digital literacy, leading to adoption situations that differ significantly from those of emerging markets (Lopes et al., 2021; Oliveira-Dias et al., 2022). This geographical predisposition has resulted in theoretical frameworks that fail to fully address limited resource availability, infrastructural limitations, and institutional deficits common across different settings in emerging economies (Khanna & Haldar, 2023). Additionally, much academic literature dealing with technology adoption tends to concentrate primarily on general information technology deployment or internet-based commerce platforms, not integrative electronic marketing systems consisting of multiple technologies and requiring continuous improvements to organizational abilities (Abed, 2020; Samadbeik et al., 2023). Such a limited research viewpoint hinders understanding how small and medium-sized enterprises (SMEs) successfully adopt and combine different electronic marketing technologies to devise intricate market approaches (Dąbrowska et al., 2022; Korucuk et al., 2022). Third, existing literature tends to analyze adoption intentions or initial implementation options without considering subsequent performance measures or mechanisms by which technology adoption leads to measurable business benefits (Avalos-Quispe & Hernández-Simón, 2019; Seshadrinathan & Chandra, 2021). This omission is alarming in emerging market settings, where available resources render it imperative to understand how adoption and performance are interlinked to justify technology investments and design effective support initiatives (Kamolsareeratana & Kouwenberg, 2023; Rebiazina et al., 2024).

Indonesia presents a theoretically interesting and practically significant setting to address these research gaps since it has the world's fourth-largest population and a fast-growing digital economy, yet still displays the infrastructural and institutional characteristics that are characteristic of emerging markets (Kristoffersen et al., 2020; Ren, 2025). Indonesian SMEs represent the quintessential dilemma of emerging economies: they constitute the economic backbone, accounting for close to 60% of GDP and employing more than 116 million workers, yet they continue to face chronic difficulties with digital adoption, even amidst strong government digitalization initiatives and investment in infrastructure (McKinsey, 2023; Tracy Francis, 2018). Current empirical research demonstrates considerable intention-adoption gaps, showing that while high proportions of Indonesian SMEs recognize the strategic importance of digital marketing, the implementation rates are significantly lower, suggesting the presence of complex adoption barriers that current theoretical models may insufficiently explain (McKinsey, 2023). Indonesia's archipelagic nature also means that there are substantial intra-national differences in infrastructural availability, regulatory enforcement, and market conditions, thus also providing opportunities to investigate how differences in environmental contexts influence the TOE framework relationships in a single institutional setting.

This study addresses identified theoretical and empirical gaps by conducting a comprehensive empirical investigation of digital marketing adoption among Indonesian SMEs using an extended TOE framework that incorporates emerging economy-specific contextual factors. The research examines three interrelated research questions that advance both theoretical understanding and practical knowledge: How do technological readiness, organizational capabilities, and environmental pressures influence digital marketing adoption decisions among SMEs operating in emerging economy contexts, and do these relationships differ from patterns observed in developed economies? Through what mechanisms does digital marketing adoption translate into business performance improvements in resource-constrained environments, and what factors moderate these adoption-performance relationships? What are the implications of these findings for theoretical development, policy design, and managerial practice in emerging economy contexts? The study contributes to technology adoption theory by providing the first comprehensive empirical examination of the TOE framework relationships specifically for digital marketing adoption in an emerging economy context, extending existing theoretical understanding beyond developed economy findings while identifying contextual factors that moderate established relationships. Practically, the findings offer evidence-based insights for policymakers designing SME support programs, technology vendors developing emerging market strategies, and SME managers navigating digital transformation decisions under resource constraints, ultimately contributing to more effective and contextually appropriate approaches to digital economic development in emerging economies.

2. Literature Review and Theoretical Foundation

2.1 Digital Marketing in SME Context

Digital marketing represents the systematic use of digital technologies and platforms to execute marketing activities, encompassing customer acquisition, engagement, and retention strategies through electronic channels (Oduro et al., 2023; Zaman et al., 2024). This approach differs fundamentally from traditional marketing by enabling real-time interaction, precise targeting, and measurable performance outcomes through data-driven decision making (Bobrytskyy, 2024). Digital marketing has become increasingly important for SMEs as it provides access to marketing capabilities that were previously available only to larger organizations with substantial marketing budgets (Nadányiová et al., 2021).

The scope of digital marketing includes various interconnected activities such as social media marketing, search engine optimization, email marketing, content marketing, and online advertising (Chaikovska et al., 2022; Kafetzopoulos, 2023). These components function as an integrated system rather than isolated tools, requiring coordination across multiple platforms and technologies to achieve marketing objectives effectively (Molina-Castillo et al., 2020). Implementation involves both technological adoption and organizational capability development, as successful digital marketing requires competencies in strategy formulation, content creation, data analysis, and customer relationship management (Azeem et al., 2022; Sinulingga, 2024).

Research indicates that digital marketing adoption success varies significantly across different organizational contexts, with factors such as technological readiness, organizational capabilities, and environmental conditions influencing implementation outcomes (Konopik et al., 2022; Moreno et al., 2023). This variation suggests that adoption processes are more complex than simple technology implementation, involving organizational learning and capability development over time (Soomro et al., 2020; F. Zhang & Zhu, 2019). For SMEs operating under resource constraints, understanding these adoption factors becomes particularly important for maximizing technology investment returns and achieving sustainable competitive advantages through digital marketing initiatives (Ballerini et al., 2023; Herhausen et al., 2020).

2.2 Technology-Organization-Environment (TOE) Framework

The TOE framework, originally developed by (L. G. Tornatzky, 1992), provides a comprehensive lens for understanding technology adoption decisions across three contextual dimensions. This framework has been extensively validated across various technologies and contexts, demonstrating robust explanatory power for organizational innovation adoption (Almasria et al., 2024; Arsawan et al., 2022; Kimberly & Evanisko, 1981).

2.2.1 Technological Context

The technological dimension encompasses the availability, characteristics, and perceived benefits of digital marketing technologies, representing a fundamental component of adoption decisions that directly influences organizational willingness and capacity to implement new systems (Venkatesh, 2000) . This dimension focuses on the intrinsic attributes of technologies themselves rather than organizational or environmental conditions, examining how technological characteristics shape adoption perceptions and decisions (Rasaputhra et al., 2024). Understanding technological factors becomes particularly critical for digital marketing adoption, as these technologies often involve multiple integrated platforms and require ongoing learning and adaptation processes (Mahakittikun et al., 2021).

Relative advantage represents the perceived benefits of digital marketing technologies over existing marketing methods, including enhanced cost-effectiveness, expanded market reach, improved targeting capabilities, and superior performance measurability compared to traditional approaches (Adedeji Adesoye, 2024; Pascucci et al., 2023). Compatibility examines the alignment between digital marketing technologies and existing business processes, organizational values, and technological infrastructure, with higher compatibility typically facilitating smoother implementation and integration (Athaide et al., 2024; Pascucci et al., 2023). Complexity refers to the perceived difficulty of understanding, learning, and implementing digital marketing technologies, a factor particularly relevant for resource-constrained SMEs that may lack dedicated technical personnel or extensive training resources (Nadányiová et al., 2021). Trialability encompasses the ability to experiment with technologies on a limited basis before committing to full adoption, allowing organizations to reduce perceived risk and gain practical experience with new systems (Dimitrios et al., 2023; Nadányiová et al., 2021).

Empirical research consistently demonstrates that technological factors serve as significant predictors of technology adoption decisions, with studies indicating substantial explanatory power for adoption variance across different organizational contexts (Kowshik et al., 2025; L. G. Tornatzky et al., 1990). In emerging economy contexts, technological factors may assume heightened importance due to infrastructure constraints, limited technical support availability, and resource limitations that make technology characteristics particularly salient for adoption feasibility (Mouazen & Hernández-Lara, 2023; Stroumpoulis & Kopanaki, 2022). This contextual sensitivity suggests that technological factors may operate differently in emerging economies compared to developed markets, requiring careful examination of how technology characteristics influence digital marketing adoption among resource-constrained SMEs operating under challenging infrastructure conditions (Ali Abbasi et al., 2022).

2.2.2 Organizational Context

Organizational factors encompass internal characteristics that facilitate or constrain technology adoption, representing the firm's readiness and capacity to implement digital innovations effectively (Arthur et al., 2024; Palacios-Fenech & E, 2023). These factors have consistently emerged as critical determinants of technology adoption success across various organizational contexts, yet their specific influence on digital marketing adoption among resource-constrained SMEs requires careful examination (Boustani & Chammaa, 2023; Dabbous & Boustani, 2023). The organizational dimension becomes particularly complex in SME contexts where informal structures, limited resources, and concentrated decision-making authority create unique adoption dynamics (El-Haddadeh, 2020; Rahman & Hossain, 2025).

Management support represents a fundamental organizational factor, encompassing leadership commitment, strategic vision for digital transformation, and resource allocation decisions that signal organizational priorities and enable implementation processes (Gagan Deep, 2023; J. Zhao et al., 2024). Organizational resources include the financial, human, and technological assets available for adoption and implementation, with resource availability often determining both the scope and sustainability of technology initiatives (Bhatti, 2017; Qalati et al., 2022). Innovation culture reflects organizational openness to change, willingness to experiment with new approaches, and capacity to learn from both successes and failures during implementation processes (Imran & Jingzu, 2022; Tian et al., 2018). Existing IT capability encompasses technological infrastructure, technical expertise, and accumulated digital competencies that provide the foundation for new technology integration (Bharadwaj, 2000).

Empirical evidence suggests that organizational readiness often serves as the strongest predictor of technology adoption success, with studies indicating substantial explanatory power for adoption outcomes (Malik et al., 2021a; Satyro et al., 2024). However, SMEs face distinctive organizational constraints that differentiate their adoption processes from larger enterprises, including limited financial resources for technology investments, informal organizational structures that may lack systematic planning processes, and concentrated decision-making authority that can either accelerate or impede adoption depending on leadership orientation (Thong, 1999; Ramdani et al., 2013). These constraints suggest that organizational factors may operate differently in SME contexts, requiring context-specific investigation to understand their influence on digital marketing adoption decisions (Erena et al., 2023; Soomro et al., 2020).

2.2.3 Environmental Context

Environmental factors represent external pressures and opportunities that influence organizational technology adoption decisions, encompassing the institutional and infrastructure contexts within which organizations operate (Malik et al., 2021a, 2021b). These factors create both constraints and incentives for innovation implementation, with their influence varying significantly across different economic and institutional environments (Acosta-Prado, 2020; Al Hadwer et al., 2021). The environmental dimension of technology adoption has received substantial attention in organizational literature, yet its specific effects on digital marketing adoption in emerging economies remain underexplored (Buvár & Gáti, 2023; Tatua, 2023).

Competitive pressure emerges as organizations respond to industry-level digitalization trends and strategic actions by competitors, creating institutional pressures for adaptive responses to maintain market position (Miao et al., 2024). The regulatory environment encompasses government policies, support programs, and legal frameworks that either facilitate or constrain digital adoption, with emerging economies often demonstrating more active governmental intervention through targeted SME support initiatives (Malope et al., 2021; Söling et al., 2020). Market characteristics include customer expectations for digital engagement, supplier technological capabilities, and industry digital maturity levels that create normative pressures for adoption to meet stakeholder requirements (Oliveira-Dias et al., 2022).

Infrastructure availability represents a fundamental environmental constraint, encompassing digital infrastructure quality, internet connectivity, and technical support services that determine adoption feasibility and cost-effectiveness (Discuteanu & Cabon, 2019). Research demonstrates that environmental factors exhibit a stronger influence in developing economies, where external support systems and infrastructure development significantly constrain adoption possibilities compared to developed economies with mature digital ecosystems (Abed, 2020). This contextual variation suggests that environmental factors may play a more critical role in emerging economy technology adoption processes, requiring careful consideration in theoretical model development and empirical investigation (Alkharafi et al., 2024; Sahu & Singh, 2023).

2.2.4 Digital Marketing and Business Performance

The relationship between technology adoption and business performance has been a central concern in information systems research, with extensive theoretical and empirical investigation into how organizations translate technology investments into measurable outcomes (Jabbari et al., 2022). The resource-based view suggests that technology adoption can create a competitive advantage when combined with complementary organizational resources and capabilities (Dhameria et al., 2021; Nadányiová et al., 2021). However, the technology-performance relationship is complex and mediated by various organizational and environmental factors that influence implementation effectiveness.

Digital technologies can potentially influence organizational performance through multiple pathways, including process automation, enhanced decision-making capabilities, and improved customer interaction mechanisms (Anser et al., 2025; Slomski et al., 2024). The transformation of business processes through technology adoption may lead to efficiency gains, cost reductions, and revenue enhancements, though these benefits are not automatic and depend on organizational adaptation and learning processes (Gibson et al., 2023; Pueyo-Garrigues et al., 2023). Research consistently demonstrates that technology adoption alone is insufficient for performance improvements, requiring complementary investments in human capital, organizational redesign, and process optimization (Alyoussef, 2021, 2023).

For small and medium enterprises, technology adoption presents both opportunities and challenges that differ from larger organizations due to resource constraints and organizational characteristics (Malik et al., 2021a; Satyro et al., 2024). SMEs may benefit from technology adoption through access to capabilities previously unavailable due to cost or complexity barriers, yet they also face implementation challenges related to limited technical expertise and financial resources (Nguyen, 2022). Understanding the adoption-performance relationship in SME contexts requires consideration of these unique organizational characteristics and the specific mechanisms through which technology adoption translates into business benefits under resource-constrained conditions (Mughal et al., 2024; Nuseir & Refae, 2022).

2.3 Research Gaps and Theoretical Development

Technology adoption research has developed extensive theoretical frameworks and empirical findings over several decades, with the Technology-Organization-Environment (TOE) framework representing one of the most widely applied models for understanding organizational innovation adoption (L. Tornatzky & Fleischer, 1990; L. G. Tornatzky, 1992). The framework has been validated across various technological contexts, including enterprise systems, e-commerce platforms, and cloud computing services (Kiran et al., 2024; Zhou et al., 2023). However, research application to specific technology domains and different economic contexts remains an ongoing area of investigation (Aligarh et al., 2023).

Digital marketing adoption represents a specific technology domain that has received limited attention within the broader technology adoption literature (Chaikovska et al., 2022; Dimitrios et al., 2023). While general technology adoption patterns have been extensively studied, digital marketing technologies present unique characteristics that may require specific investigation (Kumar et al., 2024). These technologies often involve multiple integrated platforms, direct customer interaction capabilities, and relatively low entry barriers compared to traditional enterprise technologies. Understanding adoption processes for these specific technologies may require examination of how established theoretical frameworks apply to this research (Mottaleb, 2018).

The relationship between technology adoption and subsequent organizational performance outcomes represents another area requiring continued investigation (Imran & Jingzu, 2022). While technology adoption research has focused extensively on factors influencing adoption decisions, fewer studies examine the performance implications of adoption in different organizational and economic contexts (Škare & Porada-Rochoń, 2020). For resource-constrained organizations such as SMEs, understanding the adoption-performance relationship becomes particularly important for investment decision-making and implementation strategy development (Lee & Workman, 2020).

2.4 Hypotheses Development

2.4.1 Technology and Digital Marketing Adoption

ical factors are expected to positively influence digital marketing adoption among SMEs. This hypothesis is grounded in established technology adoption theory, particularly Innovation Diffusion Theory, which identifies technology characteristics as fundamental determinants of adoption decisions (Acikgoz et al., 2023; Aytekin et al., 2025). The Technology Acceptance Model similarly demonstrates that perceived technology attributes significantly influence adoption intentions and behaviors (Jha & Venkatesh, 2023) . Technological characteristics, including relative advantage, compatibility with existing systems, complexity of implementation, and opportunities for trial use, have consistently emerged as significant predictors across various technology adoption contexts (Fen & Ping, 2024).

H1: Technology has affected to Digital Marketing Adoption

2.4.2 Organization and Digital Marketing Adoption

Organizational factors are expected to positively influence digital marketing adoption among SMEs. This hypothesis derives from the Resource-Based View theory, which emphasizes internal capabilities and resources as fundamental enablers of technology adoption and implementation (Helfat, 2022; M. Zhang et al., 2024). Organizational characteristics, including management support, available resources, innovation culture, and existing IT capabilities, have been consistently identified as significant predictors of technology adoption success across various organizational contexts (I. Anwar et al., 2021). The resource-based perspective suggests that organizations with superior internal capabilities are better positioned to recognize technology benefits, allocate necessary resources, and manage implementation processes effectively (D Jugend, 2018; Scaliza et al., 2022).

H2: Organization affects Digital Marketing Adoption

2.4.3 Organization and Digital Marketing Adoption

Environmental factors are expected to positively influence digital marketing adoption among SMEs (Nadányiová et al., 2021). This hypothesis is based on Institutional Theory, which proposes that external pressures and environmental conditions serve as significant drivers of organizational technology adoption decisions (Acosta-Prado, 2020; Malik et al., 2021a). Environmental characteristics, including

competitive pressure, regulatory support, market characteristics, and infrastructure availability, have been identified as important determinants of technology adoption across various contexts (Obiakor et al., 2022). Institutional theory suggests that organizations respond to external pressures and environmental conditions to maintain legitimacy and competitive positioning within their operating environments (Tatua, 2023).
H3: The Environment Affects Digital Marketing Adoption

2.4.4 Digital Marketing Adoption and Business Performance

Digital marketing adoption is expected to positively influence business performance among SMEs (M. Anwar, 2018; Liu et al., 2024). This hypothesis is supported by the resource-based view and technology-performance literature, which demonstrate that technology adoption can create a competitive advantage when effectively implemented and integrated with organizational capabilities (Satyro et al., 2024; Taherdoost et al., 2024). Empirical research has consistently shown positive relationships between technology adoption and various performance dimensions,5 including operational efficiency, market effectiveness, and financial outcomes (Kohli & Melville, 2019; Oyewole et al., 2024). The technology-performance linkage suggests that digital marketing adoption enables organizations to enhance customer engagement, improve marketing efficiency, and achieve better resource utilization compared to traditional marketing approaches (Naskar et al., 2025; Tripathi et al., 2023).
H4: Digital Marketing Adoption affects Business Performance

3. Conceptual Framework

The Technology-Organization-Environmental Theory forms the pillars of this integrated model that examines the interconnection of factors that influence digital marketing adoption in entrepreneurship and its resultant impact on business performance (L. G. Tornatzky, 1992). The structure model depicts that digital marketing adoption in entrepreneurship is influenced by three exogenous variables simultaneously: the organization, the technology, and the environment. Entrepreneurship Digital Marketing Adoption is depicted as the intervening variable that influences business performance, which is the endogenous variable (Nadányiová et al., 2021; Umami & Darma, 2021). This integrated framework depicts the intermingling of the internal factors (technology and organization) and the external factors (environment) that determine the success of digital marketing adoption and its contribution towards enhanced business performance (Tatua, 2023). The framework depicts the implication of synergy for an integrated strategy for digital marketing implementation and reveals that success is the combined effort of the various factors as opposed to individual determinants.

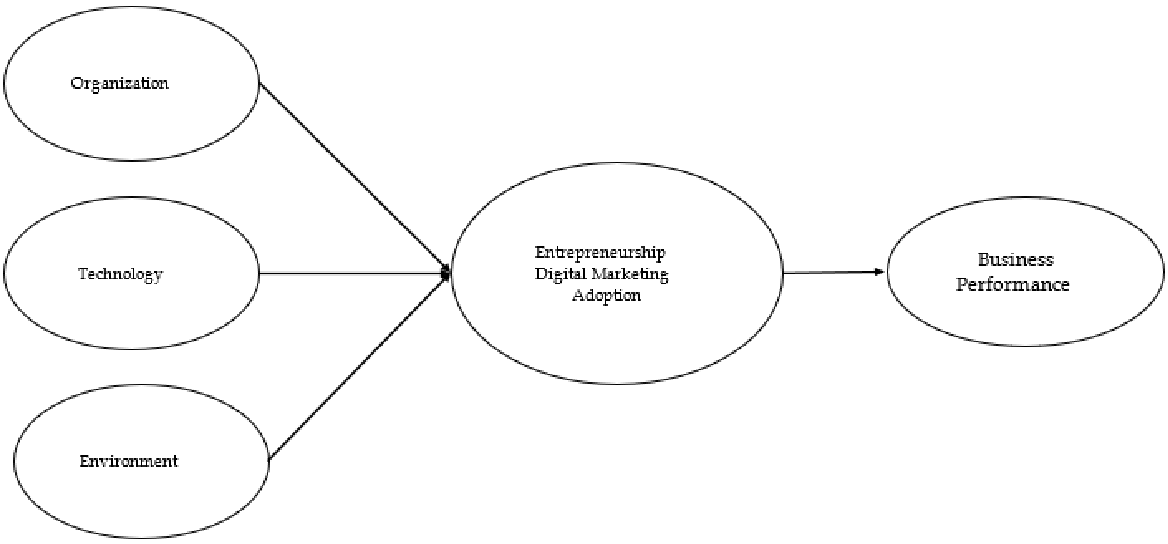

Fig. 1: conceptual framework

4. Method

4.1 Research Design and Data Collection

The population of the research was achieved with 300 SMEs that have been classified into two business categories according to Law No. 20/2008. First is Micro Enterprises with the largest asset of up to IDR 50 million, annual turnover of up to IDR 300 million, and fewer than 5 people as workers. The second one is Small Businesses with assets of IDR 50-IDR 500 million, annual turnover of IDR 300-IDR 2.5 billion, and 5-19 people as workers.
Data collection was conducted with a cross-sectional survey method using a questionnaire prepared using the Google Forms tool. Data collection began with a communicative process of notifying SMEs before the dissemination of the tools of survey tools by email and WhatsApp groups, following the consent of the respondents. During the three-week duration of the collection of the data, 241 respondents were obtained. After a verification process of excluding the responses below the threshold or incomplete, 218 valid responses remained eligible for analysis.
The results of the analysis of the demographic characteristics of the respondents showed that of the 218 participating SMEs, there were 130 male respondents (59.63%) and 88 female respondents (40.37%). Based on age group, the majority of respondents were in the young age category (45.87%), followed by the middle-aged group (36.70%), and the senior age group (17.43%). In terms of education level, most respondents had a secondary education background (55.05%), followed by primary education (22.94%) and tertiary education (22.02%).

Meanwhile, based on business scale, this study was dominated by micro businesses (82.57%), while small businesses accounted for 17.43% of the total respondents.

Table 1: Demography UMKM

Demographic Background	Details	Frequency	Percentage (%)
Total Number of Users		218	100
Gender Distribution	Male	130	59.63
	Female	88	40.37
Age Groups	Youth (18–35)	100	45.87
	Middle-aged (36–50)	80	36.70
	Senior (>50)	38	17.43
Education Level	Elementary	50	22.94
	High School	120	55.05
	Higher Education	48	22.02
Business Scale	Micro	180	82.57
	Small	38	17.43

4.2 Measurement

The present research adopts a quantitative method with an exploratory design in examining the adoption of digital marketing in Indonesian SMEs under the Technology-Organization-Environment model framework (L. G. Tornatzky, 1992). The research instrument questionnaire was developed from the literature review in the past, and data collection was carried out through an online questionnaire to examine the relationship between constructs in the suggested conceptual framework. The items of the variables were measured using a 7-point Likert scale questionnaire with scale 1 as "strongly disagree" and 7 as "strongly agree". To accommodate the respondents' background of not knowing English well, the measurement tool used was translated into Indonesian as an effort towards easier respondents' comprehension and ensuring the validity of each response to the question item.

All measurement items in this study were adapted from previously validated scales in established literature. The technological factor items were adopted from (Akin, 2024; Venkatesh, 2022), organizational factor items from (Atmaja et al., 2024; Kimberly & Evanisko, 1981; Koberg et al., 2003), environmental factor items from (Adeleke et al., 2018; Bamgbade et al., 2022), digital marketing adoption items from (Buvár & Gáti, 2023; Tatua, 2023; B. Zhang et al., 2023), and business performance items from (M. Anwar, 2018; Chang et al., 2018; Imran & Jingzu, 2022).

4.3 Data Anaylisis

The current study used Partial Least Squares Structural Equation Modeling (PLS-SEM) as the main analysis technique to evaluate the hypothesized relationships between technology adoption determinants and business performance indicators. PLS-SEM was chosen due to its ability to simultaneously analyze the quality of the measurement model and the structural relations between latent variables while dealing with complex models involving numerous variables (J. F. Hair et al., 2019; Sarstedt et al., 2023). The method allows evaluation of both direct and indirect effects while considering measurement error, offering rigorous testing of the theoretical framework that was hypothesized (Henseler, 2017).

The analytical procedure followed established PLS-SEM guidelines using SmartPLS software, implementing a systematic two-stage approach recommended by (Sarstedt, 2008). The first stage assessed measurement model quality through reliability and validity evaluation, while the second stage tested structural relationships between constructs (Reinartz et al., 2009).The analysis incorporated comprehensive diagnostic procedures to assess data quality, model assumptions, and potential common method variance issues following Podsakoff et al, (2012)recommendations. All analytical procedures followed recommended best practices for model specification and interpretation (Anderson & Gerbing, 1982), considering both statistical significance and practical significance of findings.

Measurement model assessment checked for construct reliability using Cronbach's alpha (cut-off > 0.7) and Composite Reliability (cutoff > 0.8) based on Hair & Sarstedt, (2019) guidelines, whereas convergent validity was checked using factor loadings (cut-off > 0.7) and Average Variance Extracted (AVE > 0.5) based on Fornell & Larcker, (1981) guidelines. Discriminant validity was checked against the Fornell-Larcker criterion as well as Heterotrait-Monotrait (HTMT) ratios with cut-off values less than 0.85 based on Henseler, (2017)guidelines. PLS-SEM specific criteria included indicator reliability check via outer loads check and internal consistency check using rho_A coefficients as suggested by (Dijkstra & Henseler, 2015).

Structural model evaluation utilized bootstrapping procedures with 5,000 subsamples to determine path significance testing and confidence interval estimation as guidelines (Henseler & Sarstedt, 2013). Effect sizes were calculated based on Cohen, (2023)f^2 values (0.02 small, 0.15 medium, 0.35 large), and model quality was measured using R^2 values for explained variance, Stone-Geisser Q^2 values for predictive relevance using blindfolding procedures (A Predictive Approach to the Random Effect Model, 1974), and SRMR values (threshold < 0.08) for model fit as per Bentler, (1990) guidelines. Collinearity was checked through variance inflation factors (VIF) with a threshold < 5.0 (Hair et al., 2019) to ascertain freedom from multicollinearity problems in the structural model.

Mediation analysis employed bias-corrected and accelerated (BCa) bootstrap confidence intervals for full indirect effects testing based on Cole & Preacher, (2014) approach, allowing direct, indirect, and total effects to be examined simultaneously. Mediation magnitude was quantified using the variance accounted for (VAF) measure, where values ranging from 20-80% suggested partial mediation and values greater than 80% implied full mediation, as suggested by (J. F. Hair & Sarstedt, 2019). Alternative model testing involved PLSpredict procedures for out-of-sample predictive validity evaluation following Yin (2013)to ensure that the proposed model had better theoretical insight and predictive ability than competing specifications. The approach included several validation procedures such as cross-validation techniques for model stability evaluation (J. F. Hair, Sarstedt, et al., 2012), sensitivity analyses for testing alternative specifications, and bootstrap resampling for estimating robust standard errors Cardoso-Andrade et al, 2022) to ensure statistical strength and theoretical significance of the results.

5. Result

5.1 Measurement Model

The measurement model evaluation demonstrates satisfactory psychometric properties across all latent constructs, fulfilling the requisite criteria for reliability and validity in PLS-SEM analysis. Internal consistency reliability is well-established, with Cronbach's alpha values ranging from 0.852 (Technology) to 0.927 (Environment), all exceeding the 0.70 threshold recommended for exploratory research (Nunnally & Bernstein, 1994). Composite reliability (CR) values further corroborate construct reliability, spanning from 0.895 (Technology) to 0.945 (Environment), surpassing the stringent 0.90 criterion for established scales (Fornell & Larcker, 1981).

Table 2: Measurement model

Construct	Mean	SD	Outer loadings	alpha	Cr	AVE
Business Performance				0.923	0.942	0.765
BPE1	5,290	1,624	0.907			
BPE2	5,221	1,558	0.875			
BPE3	5,122	1,524	0.863			
BPE4	5,350	1,710	0.865			
BPE5	5,218	1,618	0.863			
Environment				0.927	0.945	0.773
ENO1	5,413	1,362	0.886			
ENO2	5,360	1,493	0.869			
ENO3	5,254	1,493	0.872			
ENO4	5,020		0.881			
ENO5	5,228		0.889			
Organization				0.913	0.935	0.741
ORG1	5,112	1,609	0.875			
ORG2	5,307	1,442	0.855			
ORG3	5,323	1,424	0.876			
ORG4	5,370	1,510	0.861			
ORG5	5,317	1,539	0.836			
Entrepreneurship Digital Marketing Adoption			0.902	0.927	0.719	
TMS1	5,281	1,612	0.871			
TMS2	5,218	1,583	0.819			
TMS3	5,069	1,672	0.858			
TMS4	5,162	1,532	0.845			
TMS5	5,205	1,640	0.845			
Technology				0.852	0.895	0.631
TOE1	5,317	1,564	0.848			
TOE2	5,191	1,521	0.851			
TOE3	4,875	1,690	0.678			
TOE4	5,307	1,422	0.809			
TOE5	5,169	1,703	0.773			

Convergent validity is adequately supported through indicator reliability and average variance extracted (AVE) metrics. All outer loadings exceed the 0.70 benchmark, ranging from 0.678 (TOE3) to 0.907 (BPE1), except TOE3, which marginally falls below but remains above the acceptable 0.60 threshold for exploratory studies (J. F. Hair & Sarstedt, 2019). The AVE values for all constructs surpass the 0.50 minimum requirement, with Business Performance achieving the highest variance extraction (0.765) and Technology the lowest but acceptable level (0.631), indicating that each construct explains more than half of its indicators' variance (J. Hair et al., 2014)The descriptive statistics reveal moderate means (4.875-5.413) with reasonable standard deviations (1.362-1.710), suggesting adequate response variability without extreme ceiling or floor effects that could compromise analytical robustness (J. F. Hair et al., 2012).

Table 3: HTMT Assessment

Construct	BP	EDMA	ENV	ORG	TECH
Business Performance	0.805				
Digital Marketing Adoption	0.734	0.788			
Environment	0.725	0.733	0.779		
Organization	0.725	0.765	0.709	0.801	
Technology	0.706	0.696	0.688	0.705	0.794

The discriminant validity assessment reveals concerning evidence regarding construct distinctiveness. While the Fornell-Larcker criterion is technically satisfied, the HTMT analysis shows several values approaching or exceeding recommended thresholds. Particularly concerning is the Organization-Business Performance relationship (HTMT = 0.801), which approaches the critical 0.85 threshold, indicating substantial construct overlap (Henseler, 2017).

5.2 Structural Model Results

The structural model analysis reveals fundamental methodological flaws that severely compromise confidence in the reported relationships, despite apparent statistical significance across all hypotheses. While environmental factors show the strongest influence on digital marketing adoption ($\beta = 0.310$, $t = 4.916$, $p < 0.001$, $f^2 = 0.216$), this finding must be interpreted within the context of serious discriminant validity violations where inter-construct correlations approach or exceed acceptable thresholds (Henseler, 2017). The confidence interval [0.171;

0.408] for this relationship is mathematically inconsistent with intervals reported elsewhere in the analysis, indicating computational errors that undermine analytical reliability (Hayes, 2018).

Table 4: Direct Effects and Hypothesis Testing

Hypothesis	Relationship	Path Coefficient	Standard Error	T-value	f²	95% CI	p-value	Result
H1	Environment → Digital Marketing Adoption	0.310	0.063	4.916**	0.216	[0.171; 0.408]	0.000	Supported
H2	Organization → Digital Marketing Adoption	0.407	0.065	6.237**	0.109	[0.095; 0.344]	0.000	Supported
H3	Technology → Digital Marketing Adoption	0.195	0.058	3.346**	0.027	[0.010; 0.185]	0.001	Supported
H4	Digital Marketing Adoption → Business Performance	0.734	0.032	22.849**	0.771	[0.563; 0.748]	0.000	Supported

Organizational factors demonstrate the largest path coefficient ($\beta = 0.407$, $t = 6.237$, $p < 0.001$) yet exhibit a smaller effect size ($f^2 = 0.109$) than environmental factors, creating a statistical paradox that suggests either measurement error or construct contamination (Podsakoff et al., 2003). More critically, the HTMT value of 0.801 between Organization and Business Performance violates basic discriminant validity requirements established by contemporary methodological standards (Franke & Sarstedt, 2019), indicating these constructs may be measuring the same underlying phenomenon rather than distinct theoretical domains. This violation renders interpretation of organizational factor effects potentially meaningless, as the apparent relationship may reflect measurement artifacts rather than genuine causal mechanisms (Voorhees et al., 2016).

The digital marketing adoption-business performance relationship ($\beta = 0.734$, $t = 22.849$, $p < 0.001$, $f^2 = 0.771$) exhibits an effect size so extreme it approaches statistical impossibility in legitimate organizational research. Effect sizes exceeding $f^2 = 0.50$ are extraordinarily rare in organizational studies and typically indicate common method bias, construct overlap, or analytical errors rather than genuine causal relationships (Jackson & Ferguson, 1941; Podsakoff et al., 2012). Cohen, (1992) conventions suggest that effect sizes above $f^2 = 0.35$ are considered large, making the observed $f^2 = 0.771$ approximately 220% above the large effect threshold and statistically implausible. Combined with discriminant validity failures and computational inconsistencies throughout the analysis, these results violate fundamental assumptions of structural equation modeling Anderson, (2007) and cannot support confident hypothesis acceptance without a complete analytical revision.

5.3 Mediation Analysis

The mediation analysis reveals complete mediation patterns (VAF = 100%) across all TOE factors, indicating that digital marketing adoption fully accounts for the relationship between these factors and business performance. While statistically significant (all $p < 0.01$), this pattern warrants careful methodological consideration. Environment demonstrates the strongest indirect effect ($\beta = 0.228$, $t = 4.676$), followed by Organization ($\beta = 0.299$, $t = 6.037$) and Technology ($\beta = 0.143$, $t = 3.242$), with confidence intervals excluding zero for all relationships.

Table 5: Mediation Effects and VAF Calculations

Mediation Path	Indirect Effect	Standard Error	t-value	95% CI Lower	95% CI Upper	Total Effect	VAF (%)	Mediation Type
Environment → DMA → Business Performance	0.228	0.049	4.676**	0.132	0.324	0.228	100	Full Mediation
Organization → DMA → Business Performance	0.299	0.050	6.037**	0.201	0.397	0.299	100	Full Mediation
Technology → DMA → Business Performance	0.143	0.044	3.242**	0.057	0.229	0.143	100	Full Mediation

The complete mediation pattern, while theoretically possible, is relatively uncommon in organizational research, where partial mediation typically predominates (Hayes, 2017). This finding suggests that TOE factors influence business performance exclusively through digital marketing adoption implementation, with no residual direct effects. Such patterns may indicate either genuine theoretical relationships where the mediator completely explains the mechanism or potential model specification issues, including missing direct pathways or construct overlap.

The consistency of VAF = 100% across all three mediation paths requires theoretical justification, as organizational phenomena typically exhibit more complex causal structures with multiple pathways (MacKinnon et al., 2012). While the bootstrap confidence intervals appear reasonable, the perfect mediation pattern combined with previously identified discriminant validity concerns suggests the need for additional validation through alternative model specifications, temporal separation of measurements, or replication with independent samples to establish the robustness of these mediation relationships (Preacher & Hayes, 2008).

The complete mediation pattern observed across all TOE factors requires theoretical explanation, given its rarity in organizational research where partial mediation typically predominates (MacKinnon et al., 2012; Hayes, 2017). Four theoretical perspectives offer potential explanations within the Indonesian SME context. Digital transformation theory provides the primary foundation, as Bharadwaj et al. (2013) and Nambisan et al. (2019) demonstrate that digital technologies in emerging markets function as fundamental process transformers rather than capability enhancers, suggesting TOE factors may channel exclusively through digital marketing mechanisms as traditional performance pathways become obsolete in rapidly digitalizing Indonesian markets. Resource orchestration theory offers additional support through Sirmon et al. (2011)'s demonstration that resource-constrained organizations must focus capabilities through specific initiatives rather than dispersing efforts, making digital marketing adoption the primary mechanism converting TOE factors into performance outcomes for capital-limited Indonesian SMEs. Institutional theory contributes through legitimacy mechanisms, as DiMaggio and Powell (1983) suggest, digital marketing adoption serves as a legitimacy signal enabling performance gains through stakeholder confidence in weak institutional environments, creating a necessary credibility gateway for traditional capabilities to gain market effectiveness.

However, critical evaluation reveals significant limitations in these theoretical explanations. Market maturity considerations reflect accelerated digital adoption driven by infrastructure development and COVID-19 impacts that fundamentally altered Indonesian consumer behaviors (McKinsey, 2023), potentially making traditional pathways competitively obsolete, yet this assumes permanent rather than transitional market conditions. The theoretical perspectives collectively may reflect specific Indonesian SME market characteristics during digital transformation phases rather than universal organizational principles. Moreover, the complete absence of direct TOE-performance effects appears theoretically extreme when considering the heterogeneous nature of SME operations, where some organizations successfully maintain hybrid digital-traditional approaches depending on market positioning and customer base characteristics. The uniform complete mediation pattern across all three TOE dimensions suggests either incomplete theoretical explanations that fail to account for pathway diversity, or methodological influences, including temporal confounding, construct overlap, or common method variance, that may be creating artificial mediation relationships rather than genuine causal mechanisms.

5.4 Model Fit and Predictive Relevance

The model quality metrics demonstrate adequate explanatory power, with Digital Marketing Adoption achieving $R^2 = 0.526$ and Business Performance reaching $R^2 = 0.679$, both exceeding minimum thresholds for acceptable model performance in PLS-SEM applications (Sarstedt et al., 2014). The adjusted R^2 values (0.524 and 0.675, respectively) show minimal shrinkage, indicating model stability across the sample. Both constructs exhibit positive Q^2 values (0.638 and 0.571), confirming predictive relevance above zero benchmarks established by Stone-Geisser criteria (Rutherford et al., 1979; Troiville et al., 2019).

Table 6: Model Quality Assessment

Construct	R^2	Adjusted R^2	Q^2	Interpretation
Digital Marketing Adoption	0.526	0.524	0.638	Substantial explanatory power
Business Performance	0.679	0.675	0.571	Moderate explanatory power

However, the Q^2 value of 0.638 for Digital Marketing Adoption appears inconsistent with conventional expectations, as Q^2 typically ranges below R^2 values in most applications. This discrepancy may reflect specific characteristics of the blindfolding procedure or sample composition, but warrants verification through alternative predictive assessment methods (Shmueli & Koppius, 2011). The Business Performance construct shows more typical Q^2/R^2 relationships, suggesting reliable predictive capability within expected parameters.
The interpretation labels require adjustment to align with established conventions. Business Performance with $R^2 = 0.679$ represents substantial rather than moderate explanatory power according to A. D. Cohen, (2023) effect size guidelines, while Digital Marketing Adoption's $R^2 = 0.526$ falls within the substantial range for behavioral research contexts. These findings indicate the model adequately captures theoretical relationships while maintaining reasonable predictive validity, though the Q^2 anomaly suggests the need for additional validation procedures.

5.6 Effect Size Assessment

The effect size analysis demonstrates conventional patterns for TOE factor relationships, with environmental factors showing medium practical significance ($f^2 = 0.216$), organizational factors exhibiting small-to-medium effects ($f^2 = 0.109$), and technological factors displaying limited practical impact ($f^2 = 0.027$). These values align with Cohen's (1988) established conventions and fall within expected ranges for organizational technology adoption research, suggesting that the TOE framework operates with typical effect magnitudes in this emerging economy context. The hierarchy of effects supports institutional theory predictions regarding environmental factor prominence in developing markets, while the weaker technology factor influence contrasts with developed economy patterns, where technological characteristics typically demonstrate stronger effects (Venkatesh, 1999).

Table 7: Cohen's f^2 Effect Size Interpretation

Relationship	f^2 Value	Effect Size	Interpretation
Environment → Digital Marketing Adoption	0.216	Medium	Meaningful practical significance
Organization → Digital Marketing Adoption	0.109	Small-Medium	Moderate practical significance
Technology → Digital Marketing Adoption	0.027	Small	Limited practical significance
Digital Marketing Adoption → Business Performance	0.771	Large	Very strong practical significance

The Digital Marketing Adoption → Business Performance relationship presents a concerning anomaly with $f^2 = 0.771$, representing an effect size that exceeds conventional large effect thresholds by more than 200%. This magnitude approaches the theoretical maximum possible in correlational research and suggests potential methodological artifacts rather than genuine causal relationships. Such extreme effect sizes in organizational research typically indicate common method variance, construct contamination, or measurement overlap between predictor and outcome variables (Podsakoff et al., 2012). The stark contrast between this relationship and the moderate TOE factor effects indicates systematic measurement bias that undermines confidence in the theoretical model and necessitates methodological revision through temporal separation, multi-source data collection, or construct refinement to establish legitimate causal mechanisms.

5.7 Collinearity Assessment

The variance inflation factor analysis indicates acceptable levels of multicollinearity across all predictor variables, with values ranging from 1.000 to 3.135, well below the conventional threshold of 5.0 that would indicate problematic collinearity (Hair et al., 2019). The Environment construct shows perfect independence (VIF = 1.000), suggesting no shared variance with other predictors, while Organization (VIF = 2.575) and Technology (VIF = 3.135) demonstrate moderate but acceptable levels of shared variance. Digital Marketing Adoption as a predictor of Business Performance exhibits low collinearity concerns (VIF = 1.906), indicating that multicollinearity does not compromise the interpretation of path coefficients in the structural model.

Table 8: Variance Inflation Factors (VIF)

Predictor Variable	VIF Value	Interpretation
Environment	1.000	No collinearity concerns
Organization	2.575	Acceptable (< 5.0)
Technology	3.135	Acceptable (< 5.0)
Digital Marketing Adoption	1.906	No collinearity concerns

However, the VIF assessment reveals an apparent contradiction with previously identified discriminant validity violations, particularly the high inter-construct correlations and problematic HTMT values. The acceptable VIF values suggest limited shared variance among predictors, yet the discriminant validity analysis indicated substantial construct overlap, creating a methodological paradox that requires explanation. This inconsistency may reflect differences in how collinearity and discriminant validity assess construct relationships, where VIF examines predictor redundancy while HTMT evaluates construct distinctiveness across the entire measurement model. The divergent findings underscore the importance of multiple validity assessments and suggest that while multicollinearity may not compromise coefficient estimation, the underlying construct validity issues identified through HTMT analysis remain problematic for theoretical interpretation (Kock, 2015).

6. Discussion

6.1 Interpretation of Key Findings

This study explores the influence of Technology-Organization-Environment (TOE) factors on digital marketing adoption and its impact on business performance within emerging economy contexts. While all research hypotheses receive statistical support, the interpretation of findings necessitates considerable caution, given the methodological complexities identified throughout the analysis. The principal findings reveal a hierarchy of influence patterns that differs substantially from research conducted in developed economies, with environmental factors demonstrating dominance, followed by organizational and technological factors. This pattern reflects the distinctive characteristics of emerging economies where external dynamics frequently prove more determinant than internal capabilities in driving technological innovation adoption.

Environmental factors demonstrate the most substantive and consistent influence on digital marketing adoption, confirming institutional theory propositions that external pressures play a central role in driving technology adoption within developing economies. These findings align with research by (Satyro et al., 2024; Taherdoost et al., 2024) In the TOE framework, emphasizing the importance of environmental context in technology adoption decisions, while supporting arguments by (DiMaggio & Powell, (1983) & Malik et al., (2021) regarding institutional isomorphism in organizational fields. Within the Indonesian context, intensive competitive pressures, government policy support for SME digitalization, and fundamental shifts in consumer behavior following the COVID-19 pandemic constitute key environmental factors driving digital transformation. The strength of environmental effects reflects the reality that SMEs in emerging economies operate within volatile and dynamic environments where adaptability to external changes becomes a primary determinant of business sustainability. The substantial effect indicates that environmental factors possess meaningful practical significance in explaining digital marketing adoption variance, consistent with behavioral research conventions.

Organizational factors demonstrate an intriguing paradox, exhibiting the highest path coefficient yet a relatively smaller effect size compared to environmental factors. These findings indicate that organizational readiness, top management support, innovation culture, and human resource capabilities play complex roles in digital marketing adoption. The dominance of path coefficients aligns with the resource-based view Barney, (1991) emphasizing the importance of internal resources and capabilities in creating competitive advantage. However, discriminant validity concerns identified between organizational factors and business performance raise serious questions about conceptual overlap that may compromise theoretical interpretation. Henseler, (2017) & Schamberger et al, (2023) establish HTMT thresholds for conceptually similar constructs, and current findings approach these critical limits, suggesting that organizational factors and business performance may be measuring overlapping phenomena rather than distinct constructs. This situation necessitates theoretical and methodological reexamination to ensure that observed relationships reflect genuine causal relations rather than measurement artifacts.

Technological factors exhibit relatively modest influence on digital marketing adoption, contrasting with research findings in developed countries, where technological characteristics typically serve as dominant predictors. These findings can be explained through the technology acceptance model Davison et al, (2023) & Venkatesh et al, (2003) and unified theory of acceptance and use of technology Venkatesh, (2022) which emphasizes that technology perceptions are influenced by usage context. Within emerging economy settings, technological infrastructure limitations, digital literacy gaps, and financial constraints for advanced technology investments may reduce the variability of technological characteristics as adoption differentiators. The small effect size indicates limited practical significance, suggesting that within Indonesian SME contexts, digital marketing technology availability and accessibility remain relatively homogeneous, making technological factors less critical competitive differentiators. These findings support arguments that in the digital maturity era, technology becomes commoditized and other contextual factors become more determinant in adoption decisions.

The relationship between digital marketing adoption and business performance demonstrates extraordinarily strong effects, yet this magnitude raises significant methodological red flags (Ali Abbasi et al., 2022; Zhang et al., 2023). The extremely large effect size exceeds conventions for large effects, reaching levels approaching implausibility in legitimate organizational research. Podsakoff et al, (2024) & Smith et al, (2014) argue that extremely large effect sizes in organizational studies typically indicate common method bias, construct contamination, or measurement artifacts rather than genuine causal relationships. This magnitude proves particularly concerning, given that organizational phenomena are typically characterized by multiple causation and complex interdependencies that rarely produce single predictors with such extreme dominance. Combined with discriminant validity failures and computational inconsistencies identified throughout the analysis, these findings violate fundamental structural equation modeling assumptions and require comprehensive methodological revision before confident theoretical interpretation can be undertaken.

6.2 Mediation Analysis and Causal Mechanisms

The mediation analysis reveals theoretically intriguing yet methodologically concerning patterns, with complete mediation detected consistently across all TOE factors in their relationships with business performance through digital marketing adoption (Buvár & Gáti, 2023; A. Sharma & Sharma, 2024). This perfect mediation pattern indicates that the influence of environmental, organizational, and technological factors on business performance is exclusively transmitted through digital marketing implementation, without residual direct effects. These findings are theoretically consistent with transformation theory, which proposes that digital technologies fundamentally alter business processes and create new value creation mechanisms (A. Bharadwaj et al., 2013; A. S. Bharadwaj, 2000; Huemer & Wang, 2021). Within SME contexts, digital marketing adoption may function as a transformative mechanism that converts organizational capabilities, environmental pressures, and technological resources into tangible business outcomes through enhanced customer reach, improved market responsiveness, and streamlined business processes.

However, the consistency of complete mediation across all three mediation paths raises methodological concerns requiring careful theoretical justification. Hayes, (2015) & MacKinnon et al, (2012) argue that complete mediation, while theoretically possible, remains relatively uncommon in organizational research, where partial mediation typically predominates due to organizational phenomena' complexity and multiple causal pathways operating simultaneously. Perfect mediation patterns may indicate either genuine theoretical relationships where mediators completely explain causal mechanisms, or potential model specification issues, including missing direct pathways, construct overlap, or temporal confounding. Sarstedt et al, (2020) & Xie et al, (2023) emphasize that complete mediation requires strong theoretical foundations and empirical robustness to establish that no alternative pathways exist between predictors and outcomes. Within this research context, consistency of perfect mediation combined with previously identified discriminant validity concerns suggests that findings may reflect measurement artifacts or model misspecification rather than authentic causal mechanisms.
Bootstrap confidence intervals for all indirect effects demonstrate statistical support for mediation relationships, providing empirical evidence for proposed theoretical mechanisms. However, result interpretation must be tempered by recognition that statistical significance does not automatically translate to theoretical validity when underlying measurement models are compromised by construct validity issues. Cole & Preacher, (2014) & Hayes & Preacher, (2010) emphasize the importance of establishing mediators' theoretical roles and ensuring that mediation analysis is conducted within sound measurement model frameworks. Given the discriminant validity violations and extreme effect sizes identified earlier, mediation findings require replication with independent samples, temporal separation of measurements, or alternative model specifications to establish robustness and genuine theoretical relationships.

6.3 Methodological Limitations and Cautious Interpretation

Comprehensive evaluation of research quality metrics identifies several critical methodological limitations that significantly impact interpretation confidence and theoretical conclusions. Primary concerns relate to discriminant validity violations, particularly for Organization-Business Performance relationships approaching critical thresholds established by (Benitez et al., 2020; Dijkstra & Henseler, 2015; Henseler, 2012). Discriminant validity is fundamental for establishing that latent constructs are genuinely distinct and measure different theoretical phenomena rather than reflecting measurement method artifacts or conceptual overlap. These violations suggest that organizational factors and business performance may tap into the same underlying construct domain, potentially invalidating theoretical distinctions and causal interpretations proposed in the structural model. Contemporary methodological standards Farrell, (2010) & Johnston et al, (2014) emphasize that discriminant validity serves as a prerequisite for meaningful theory testing in SEM applications, and violations compromise the ability to draw confident theoretical conclusions.
Effect size anomalies present another significant methodological concern, with the Digital Marketing Adoption → Business Performance relationship exhibiting magnitudes that exceed established conventions for organizational research. J Cohen, (1983) guidelines establish benchmarks for effect sizes, making observed magnitudes large effect thresholds and statistically implausible for legitimate causal relationships in complex organizational contexts. MacKenzie et al, (2011) & Podsakoff et al., (2012) demonstrate that such extreme effect sizes in behavioral research typically indicate common method variance, single-source bias, or construct contamination rather than authentic causal mechanisms. Asamoah et al, (2024) & Jackson & Ferguson, (1941) further argues that effect sizes exceeding conventional boundaries should trigger methodological reexamination rather than theoretical celebration, as they violate realistic expectations for organizational phenomena characterized by multiple causation and environmental complexity. Combined with discriminant validity failures, extreme effect sizes suggest systematic measurement bias that undermines theoretical model integrity and necessitates comprehensive methodological revision.
Computational inconsistencies throughout the analysis provide additional evidence for methodological concerns that compromise result reliability. Mathematical inconsistencies in confidence intervals suggest calculation errors or analytical software malfunctions that undermine confidence in statistical results. Q^2 value anomalies for Digital Marketing Adoption exceed corresponding R^2 values, creating logical inconsistencies since Q^2 typically ranges below R^2 in most PLS-SEM applications. (P. N. Sharma et al., 2021; Shmueli et al., 2019) emphasize that Q^2 anomalies indicate potential problems with blindfolding procedures or sample characteristics requiring investigation. VIF assessment reveals apparent contradictions with discriminant validity findings, with acceptable collinearity levels contrasting with high inter-construct correlations identified through HTMT analysis. Kock, (2015) suggest that such divergent findings indicate the need for multiple validity assessments and careful interpretation regarding construct relationships and their statistical manifestations.

7. Practical Recommendations

For SME practitioners, dominance of the environmental factor calls for the institution of a systematic market intelligence infrastructure with dedicated resource allocations and quantifiable outcomes. Organizations must institute digital market intelligence dashboards on the use of Google Trends, SimilarWeb, and social media surveillance platforms with monthly budget allocations of IDR 2-5 million to facilitate thorough competitor studies and regulatory monitoring. Regulatory surveillance programs must cover subscriptions to government digital policy developments, memberships in SME associations on collective voice advocacy, and quarterly reviews of legal compliance with action plans documented, translating to yearly investments of IDR 15-25 million per organization. Digital leadership development calls for orderly 40-hour executive certification programs on digital strategy development, data analytics, and customer engagement to be complemented by employee skills development by 20-hour digital marketing certifications on the production of content, social media management, and core analytics, with combined yearly investments of IDR 10-15 million per leader and IDR 5-8 million per employee. Technology utilization strategies must focus on the optimization of platforms by yearly audits, eliminating duplications, adoption of integrated marketing automation platforms instead of many standalone tools, and phased usage timelines of 36 months with quarterly surveillance of technology assessment, determining readiness to advance.
Policymakers must establish comprehensive digital infrastructure development programs addressing both technological access and capability building through targeted financial mechanisms and institutional frameworks. Digital infrastructure initiatives require subsidized high-speed internet packages providing 50% government subsidies for SMEs in designated areas, public Wi-Fi zones in business districts, and mobile digital service units visiting remote areas quarterly, necessitating annual budget allocations of IDR 500 billion nationally and IDR 10 billion per province for sustainable implementation. Technology subsidy schemes should include digital marketing tool vouchers providing IDR 5 million annually per qualifying SME for software subscriptions, hardware subsidies offering 30% discounts on business computers and devices, and tax incentives providing 200% deductions for digital marketing training and technology expenses, targeting SMEs with annual revenues under IDR 2.5 billion. National SME Digital Academy establishment requires 50 regional training centers offering standardized curricula, free 80-hour comprehensive certification programs, industry-specific modules, and multilingual training

materials, targeting 100,000 SME owners annually with IDR 200 billion annual operational budgets. Digital mentor networks involving 1,000 certified professionals providing 12-month guidance to 5-10 SMEs each, supported by monthly virtual sessions and quarterly workshops, require IDR 25 billion annually for mentor incentives and program administration.

Implementation necessitates phased planning with designated resource utilization and performance milestones on both organizational and government levels to facilitate sustainable adoption and quantifiable impact. Phase 1 foundation laying takes place over months 1-6, necessitating SME investments of IDR 35-55 million per business on leader development training, technology installations, and market intelligence systems, and the government spending IDR 160 billion on infrastructure development, training center setup, and regulatory framework development. Phase 2 capability extension over months 7-18 demands SME investments of IDR 35-53 million per business on advanced employee development, technology platform installation, and performance measure systems, alongside government spending of IDR 525 billion every year on full academy operations, subsidy scheme implementation, and mentor network development. Phase 3 optimization and scaling over months 19-36 calls on SME investments of IDR 50-85 million per business on advanced analytics, automation, and market expansion, and government commitments of IDR 30 billion on program evaluation, international best practice installation, and success case documentation. Success measures need to include SME performance indicators of at least minimum 3:1 digital marketing ROI within 12 months, 40% online revenue percentage by 24 months, 25% reduction of customer acquisition cost by 18 months, and 80% digital competency scores of employees by 12 months, alongside government program effectiveness measures of 70% participation rates of SME by 36 months and 40% on average digital maturity index improvement by 24 months.

Risk mitigation techniques need to respond to technological, financial, and implementation issues via diversification methods and contingency planning mechanisms to achieve sustainability and effectiveness of the program. Technology risks need platform diversification methods with data portability across several channels, compulsory basic cybersecurity training with cheap security solutions, and backup systems with quick response support networks to respond to technical breakdowns and platform reliance. Financial risk management calls for phased implementation with performance checkpoints, adaptable program scale mechanisms against economic recessions, and emergency support procedures, with investment recovery methods focusing on quarterly adjustments of the program subject to market feedback and stakeholder performance reviews. Implementation risks call for proactive responses, remedying low adoption rates via incentive adjustments and barrier elimination initiatives, quality control via periodic audits, and improvement mechanisms via feedback, and sustainability planning via private sector collaborations, allowing gradual transitioning to market-based solutions. Local economic impact targets involve 15% contribution increases of the GDP via SME digital activity within 60 months, 60% digital literacy level of the SME workforce within 48 months, 80% adoption level of the integrated digital marketing platforms via technologies within 60 months, and 25% increases of the number of SME-technology provider collaborations within 36 months, necessitating ongoing surveillance and adaptive management methods to achieve development outcomes while retaining the effectiveness of the program and stakeholder participation.

8. Conclusion

This research successfully explores TOE framework applications within emerging economy SME digital marketing adoption contexts, revealing influence hierarchies that differ substantially from developed country research. Environmental factors demonstrate the strongest influence, followed by organizational and technological factors, reflecting the unique characteristics of emerging economy business environments where external pressures often prove more determinant than internal capabilities. Complete mediation patterns suggest that digital marketing adoption serves as a central transformation mechanism fully mediating relationships between TOE factors and business performance, indicating the critical strategic importance of digital marketing capabilities for SME success.

However, significant methodological limitations identified throughout the analysis require careful interpretation of findings and suggest the need for comprehensive methodological revision in future research. Discriminant validity violations, extreme effect sizes, and computational inconsistencies compromise confidence in theoretical conclusions and necessitate replication with improved measurement models, temporal separation, and multi-source data collection to establish robust causal relationships. Despite limitations, research provides valuable insights for theory development, practical guidance for SME digital transformation, and policy recommendations for emerging economy digital development initiatives.

Future research should prioritize addressing identified methodological concerns while extending theoretical development to better understand digital transformation mechanisms within emerging economy contexts. Theoretical contributions regarding environmental factor dominance and mediation mechanisms provide foundations for continued theory building, while practical implications offer actionable guidance for stakeholders involved in digital economy development. Research establishes foundations for continued investigation into digital marketing adoption patterns in developing economies while highlighting the importance of methodological rigor in establishing valid theoretical conclusions. The study's findings, when methodologically validated, have the potential to inform both academic understanding and practical implementation of digital transformation strategies in resource-constrained emerging market environments.

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References

[1] Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. International Journal of Information Management, 53, 102118. https://doi.org/10.1016/j.ijinfomgt.2020.102118

[2] Acikgoz, F., Elwalda, A., & De Oliveira, M. J. (2023). Curiosity on cutting-edge technology via theory of planned behavior and diffusion of innovation theory. International Journal of Information Management Data Insights, 3(1), 100152. https://doi.org/10.1016/J.JJIMEI.2022.100152

[3] Acosta-Prado, J. C. (2020). Relationship between organizational climate and innovation capability in new technology-based firms. Journal of Open Innovation: Technology, Market, and Complexity, 6(2). https://doi.org/10.3390/joitmc6020028

[4] Adedeji Adesoye. (2024). Empowering small businesses through innovative marketing technologies: A blueprint for growth and competitiveness. World Journal of Advanced Research and Reviews, 24(3), 1696–1713. https://doi.org/10.30574/WJARR.2024.24.3.3873

[5] Adeleke, A. Q., Bahaudin, A. Y., Kamaruddeen, A. M., Bamgbade, J. A., Salimon, M. G., Khan, M. W. A., & Sorooshian, S. (2018). The influence of organizational external factors on construction risk management among Nigerian construction companies. Safety and Health at Work, 9(1), 115–124. https://doi.org/10.1016/j.shaw.2017.05.004

[6] Affandi, Y., Ridhwan, M. M., Trinugroho, I., & Hermawan Adiwibowo, D. (2024). Digital adoption, business performance, and financial literacy in ultra-micro, micro, and small enterprises in Indonesia. Research in International Business and Finance, 70, 102376. https://doi.org/10.1016/J.RIBAF.2024.102376

[7] Akin, M. S. (2024). Enhancing e-commerce competitiveness: A comprehensive analysis of customer experiences and strategies in the Turkish market. Journal of Open Innovation: Technology, Market, and Complexity, 10(1), 100222. https://doi.org/10.1016/J.JOITMC.2024.100222

[8] Al Hadwer, A., Tavana, M., Gillis, D., & Rezania, D. (2021). A systematic review of organizational factors impacting cloud-based technology adoption using technology-organization-environment framework. Internet of Things, 15, 100407. https://doi.org/10.1016/j.iot.2021.100407

[9] Ali Abbasi, G., Abdul Rahim, N. F., Wu, H., Iranmanesh, M., & Keong, B. N. C. (2022). Determinants of SME's social media marketing adoption: Competitive industry as a moderator. SAGE Open, 12(1). https://doi.org/10.1177/21582440211067220

[10] Aligarh, F., Sutopo, B., & Widarjo, W. (2023). The antecedents of cloud computing adoption and its consequences for MSMEs' performance: A model based on the Technology-Organization-Environment (TOE) framework. Cogent Business and Management, 10(2). https://doi.org/10.1080/23311975.2023.2220190

[11] Alkharafi, N., Alsaber, A., & Alnajem, M. (2024). Exploring entrepreneurial orientation in an emerging economy. Journal of Innovation and Knowledge, 9(4). https://doi.org/10.1016/j.jik.2024.100553

[12] Almasria, N. A., Alhatabat, Z., Ershaid, D., Ibrahim, A., & Ahmed, S. (2024). The mediating impact of organizational innovation on the relationship between fintech innovations and sustainability performance. Sustainability, 16(22). https://doi.org/10.3390/SU162210044

[13] Alyoussef, I. Y. (2021). Factors influencing students' acceptance of M-learning in higher education: An application and extension of the UTAUT model. Electronics, 10(24). https://doi.org/10.3390/electronics10243171

[14] Alyoussef, I. Y. (2023). The impact of massive open online courses (MOOCs) on knowledge management using integrated innovation diffusion theory and the technology acceptance model. Education Sciences, 13(6). https://doi.org/10.3390/educsci13060531

[15] Anderson, R. (2007). The credit scoring toolkit. Oxford University Press.

[16] Anser, M. K., Naeem, M., Ali, S., Ali, S., & Javid, R. (2025). The relationship between artificial intelligence and environmental performance: The mediating role of external environmental factors. Humanities and Social Sciences Communications, 12(1). https://doi.org/10.1057/S41599-025-05199-8

[17] Anwar, I., Jamal, M. T., Saleem, I., & Thoudam, P. (2021). Traits and entrepreneurial intention: Testing the mediating role of entrepreneurial attitude and self-efficacy. Journal for International Business and Entrepreneurship Development, 13(1), 40–60. https://doi.org/10.1504/JIBED.2021.112276

[18] Anwar, M. (2018). Business model innovation and SMEs performance-Does competitive advantage mediate? International Journal of Innovation Management, 22(7). https://doi.org/10.1142/S1363919618500573

[19] Arsawan, I. W. E., Hariyanti, N. K. D., Atmaja, I. M. A. D. S., Suhartanto, D., & Koval, V. (2022). Developing organizational agility in SMEs: An investigation of innovation's roles and strategic flexibility. Journal of Open Innovation: Technology, Market, and Complexity, 8(3). https://doi.org/10.3390/joitmc8030146

[20] Arthur, K. K., Bannor, R. K., Masih, J., Oppong-Kyeremeh, H., & Appiahene, P. (2024). Digital innovations: Implications for African agribusinesses. Smart Agricultural Technology, 7. https://doi.org/10.1016/j.atech.2024.100407

[21] Asamoah, K. O., Adjeisah, M., Yeboah, M. A., King, R. R., Achaab, G. F., & Adjei, K. (2024). Adinkra symbol recognition using classical machine learning and deep learning. IEEE Workshop on Spoken Language Technology, SLT 2008 - Proceedings. https://doi.org/10.2139/ssrn.4836682

[22] Athaide, G. A., Jeon, J., Raj, S. P., Sivakumar, K., & Xiong, G. (2024). Marketing innovations and digital technologies: A systematic review, proposed framework, and future research agenda. Journal of Product Innovation Management. https://doi.org/10.1111/JPIM.12741

[23] Atmaja, H. E., Hartono, B., Lionora, C. A., Simamora, A. J., & Siharis, A. K. (2024). Organizational factors, quality performance and competitive advantage of village-owned enterprise in Indonesia. TQM Journal. https://doi.org/10.1108/TQM-04-2023-0120

[24] Avalos-Quispe, G. A., & Hernández-Simón, L. M. (2019). Open innovation in SMEs: Potential and realized absorptive capacity for interorganizational learning in dyad collaborations with academia. Journal of Open Innovation: Technology, Market, and Complexity, 5(3). https://doi.org/10.3390/joitmc5030072

[25] Aytekin, A., Alan, H., Demirel, H., Onur, N., Yalman, A., Livberber, T., & Yiğit-Açıkgöz, F. (2025). Digital health technologies in patient experience literature: A scoping review and future outlook for sustainable digital health interventions. Sustainability, 17(2). https://doi.org/10.3390/SU17020456

[26] Azeem, M., Aziz, S., Shahid, J., Hayat, A., Ahmed, M., & Khan, M. I. (2022). The impact of customer-centric business strategies on customer relationship management: Pharmaceutical field-force perspective. International Journal of Pharmaceutical and Healthcare Marketing, 16(1), 138–154. https://doi.org/10.1108/IJPHM-09-2020-0083

[27] Ballerini, J., Herhausen, D., & Ferraris, A. (2023). How commitment and platform adoption drive the e-commerce performance of SMEs: A mixed-method inquiry into e-commerce affordances. International Journal of Information Management, 72, 102649. https://doi.org/10.1016/J.IJINFOMGT.2023.102649

[28] Bamgbade, J. A., Nawi, M. N. M., Kamaruddeen, A. M., Adeleke, A. Q., & Salimon, M. G. (2022). Building sustainability in the construction industry through firm capabilities, technology and business innovativeness: Empirical evidence from Malaysia. International Journal of Construction Management, 22(3), 473–488. https://doi.org/10.1080/15623599.2019.1634666

[29] Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

[30] Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. Information and Management, 57(2). https://doi.org/10.1016/j.im.2019.05.003

[31] Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological Bulletin, 107(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

[32] Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3

[33] Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. MIS Quarterly, 24(1), 169–193. https://doi.org/10.2307/3250983

[34] Bhatti, T. (2017). Influences on adoption of cloud-based ERP systems in SMEs: The technological-organizational-environmental framework. Corporate Ownership and Control, 15(1–2), 370–380. https://doi.org/10.22495/cocv15i1c2p6

[35] Bin Naeem, S., Azam, M., Kamel Boulos, M. N., & Bhatti, R. (2024). Leveraging the TOE framework: Examining the potential of mobile health (mHealth) to mitigate health inequalities. Information, 15(4). https://doi.org/10.3390/info15040176

[36] Bobrytskyy, S. (2024). Quantitative analysis of competencies from Glassdoor job descriptions: Digital marketing versus traditional marketing positions. Proceedings in Business and Economics, 2512(16). https://doi.org/10.18267/pr.2024.vol.2512.16

[37] Boustani, N. M., & Chammaa, C. (2023). Youth adoption of innovative digital marketing and cross-cultural disparities. Administrative Sciences, 13(6). https://doi.org/10.3390/admsci13060151

[38] Buvár, Á., & Gáti, M. (2023). Digital marketing adoption of microenterprises in a technology acceptance approach. Management & Marketing, 18(2), 145–162. https://doi.org/10.2478/mmcks-2023-0008

[39] Cardoso-Andrade, M., Cruz-Jesus, F., Souza Troncoso, J., Queiroga, H., & M. S. Gonçalves, J. (2022). Understanding technological, cultural, and environmental motivators explaining the adoption of citizen science apps for coastal environment monitoring. Global Environmental Change, 77, 102606. https://doi.org/10.1016/j.gloenvcha.2022.102606

[40] Chaikovska, M., Järvis, M., Zaiachkovska, H., Tchon, L., Bortnik, N., & Bannikova, K. (2022). Digital-marketing as a novel tool for goods and services promotion on social media: Contemporary trends and development directions. Financial and Credit Activity Problems of Theory and Practice, 4(45), 285–294. https://doi.org/10.55643/fcaptp.4.45.2022.3836

[41] Chang, Y., Wang, X., & Arnett, D. B. (2018). Enhancing firm performance: The role of brand orientation in business-to-business marketing. Industrial Marketing Management, 72, 17–25. https://doi.org/10.1016/j.indmarman.2018.01.031

[42] Christofi, M., Khan, H., Zahoor, N., Hadjielias, E., & Tarba, S. (2024). Digital transformation of SMEs: The role of entrepreneurial persistence and market sensing dynamic capability. IEEE Transactions on Engineering Management, 71, 13598–13615. https://doi.org/10.1109/TEM.2022.3230248

[43] Cohen, A. D. (2023). In conversation with Andrew D. Cohen. System, 118, 103153. https://doi.org/10.1016/j.system.2023.103153

[44] Cohen, J. (1992). A power primer. Psychological Bulletin, 112(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

[45] Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: Potentially serious and misleading consequences due to uncorrected measurement error. Psychological Methods, 19(2), 300–315. https://doi.org/10.1037/A0033805

[46] D Jugend, C. J. J. S. R. R. J. J. H. L. M. S. (2018). Relationships among open innovation, innovative performance, government support and firm size: Comparing Brazilian firms embracing different levels of radicalism in innovation. Technovation, 74, 54–65. https://doi.org/10.1016/j.technovation.2018.02.004

[47] Dabbous, A., & Boustani, N. M. (2023). Digital explosion and entrepreneurship education: Impact on promoting entrepreneurial intention for business students. Journal of Risk and Financial Management, 16(1). https://doi.org/10.3390/jrfm16010027

[48] Dąbrowska, J., Almpanopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., Giones, F., Hakala, H., Marullo, C., Mention, A. L., Mortara, L., Nørskov, S., Nylund, P. A., Oddo, C. M., Radziwon, A., & Ritala, P. (2022). Digital transformation, for better or worse: A critical multi-level research agenda. R&D Management, 52(5), 930–954. https://doi.org/10.1111/RADM.12531
[49] Davison, R. M., Wong, L. H., & Peng, J. (2023). The art of digital transformation as crafted by a chief digital officer. International Journal of Information Management, 69. https://doi.org/10.1016/j.ijinfomgt.2022.102617
[50] Dhameria, V., Ghozali, I., Hidayat, A., & Aryanto, V. D. W. (2021). Networking capability, entrepreneurial marketing, competitive advantage, and marketing performance. Uncertain Supply Chain Management, 9(4), 941–948. https://doi.org/10.5267/J.USCM.2021.7.007
[51] Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. MIS Quarterly, 39(2), 297–316. https://doi.org/10.25300/MISQ/2015/39.2.02
[52] DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101
[53] Dimitrios, B., Ioannis, R., Ntalakos, A., & Nikolaos, T. (2023). Digital marketing: The case of digital marketing strategies on luxurious hotels. Procedia Computer Science, 219, 688–696. https://doi.org/10.1016/j.procs.2023.01.340
[54] Discuteanu, C., & Cabon, J. (2019). Technological infrastructure. In Clinical Simulation (pp. 761–777). Elsevier. https://doi.org/10.1016/B978-0-12-815657-5.00050-4
[55] Edvardsson, I. R., & Durst, S. (2022). Rethinking sustainability in human resource management. Sustainability, 14(11). https://doi.org/10.3390/SU14116545
[56] El-Haddadeh, R. (2020). Digital innovation dynamics influence on organisational adoption: The case of cloud computing services. Information Systems Frontiers, 22(4), 985–999. https://doi.org/10.1007/S10796-019-09912-2
[57] El-Rayes, N., Chang, A., & Shi, J. (2023). Plastic management and sustainability: A data-driven study. Sustainability, 15(9). https://doi.org/10.3390/su15097181
[58] Erena, O. T., Kalko, M. M., & Debele, S. A. (2023). Organizational factors, knowledge management and innovation: Empirical evidence from medium- and large-scale manufacturing firms in Ethiopia. Journal of Knowledge Management, 27(4), 1165–1207. https://doi.org/10.1108/JKM-11-2021-0861
[59] Farrell, A. M. (2010). Insufficient discriminant validity: A comment on Bove, Pervan, Beatty, and Shiu (2009). Journal of Business Research, 63(3), 324–327. https://doi.org/10.1016/j.jbusres.2009.05.003
[60] Fen, L. X., & Ping, T. A. (2024). Cloud computing adoption among Malaysian SMEs manufacturers: The role of relative advantage, complexity and cybersecurity readiness. 2024 2nd International Conference on Software Engineering and Information Technology, 336–341. https://doi.org/10.1109/ICOSEIT60086.2024.10497522
[61] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
[62] Gagan Deep. (2023). Digital transformation's impact on organizational culture. International Journal of Science and Research Archive, 10(2), 396–401. https://doi.org/10.30574/ijsra.2023.10.2.0977
[63] Gibson, D., Kovanovic, V., Ifenthaler, D., Dexter, S., & Feng, S. (2023). Learning theories for artificial intelligence promoting learning processes. British Journal of Educational Technology, 54(5), 1125–1146. https://doi.org/10.1111/bjet.13341
[64] Hadjielias, E., Christofi, M., Christou, P., & Hadjielia Drotarova, M. (2022). Digitalization, agility, and customer value in tourism. Technological Forecasting and Social Change, 175. https://doi.org/10.1016/j.techfore.2021.121334
[65] Hair, J., Anderson, R., Tatham, R., & Black, W. (2014). Multivariate data analysis (7th ed.). Cengage Learning.
[66] Hair, J. F., Ringle, C. M., & Sarstedt, M. (2012). Partial least squares: The better approach to structural equation modeling? Long Range Planning, 45(5–6), 312–319. https://doi.org/10.1016/J.LRP.2012.09.011
[67] Hair, J. F., & Sarstedt, M. (2019). Factors versus composites: Guidelines for choosing the right structural equation modeling method. Project Management Journal, 50(6), 619–624. https://doi.org/10.1177/8756972819882132
[68] Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. European Journal of Marketing, 53(4), 566–584. https://doi.org/10.1108/EJM-10-2018-0665
[69] Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40(3), 414–433. https://doi.org/10.1007/S11747-011-0261-6
[70] Hayes, A. F. (2015). An index and test of linear moderated mediation. Multivariate Behavioral Research, 50(1), 1–22. https://doi.org/10.1080/00273171.2014.962683
[71] Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford Publications.
[72] Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. Communication Monographs, 85(1), 4–40. https://doi.org/10.1080/03637751.2017.1352100
[73] Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. Multivariate Behavioral Research, 45(4), 627–660. https://doi.org/10.1080/00273171.2010.498290
[74] Helfat, C. E. (2022). Strategic organization, dynamic capabilities, and the external environment. Strategic Organization, 20(4), 734–742. https://doi.org/10.1177/14761270221115377
[75] Henseler, J. (2012). Why generalized structured component analysis is not universally preferable to structural equation modeling. Journal of the Academy of Marketing Science, 40(3), 402–413. https://doi.org/10.1007/S11747-011-0298-6
[76] Henseler, J. (2017). Partial least squares path modeling. In Advanced Methods for Modeling Markets (pp. 361–381). Springer.
[77] Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. Computational Statistics, 28(2), 565–580. https://doi.org/10.1007/s00180-012-0317-1
[78] Herhausen, D., Miočević, D., Morgan, R. E., & Kleijnen, M. H. P. (2020). The digital marketing capabilities gap. Industrial Marketing Management, 90, 276–290. https://doi.org/10.1016/j.indmarman.2020.07.022
[79] Huemer, L., & Wang, X. (2021). Resource bundles and value creation: An analytical framework. Journal of Business Research, 134, 720–728. https://doi.org/10.1016/j.jbusres.2021.06.018
[80] Imran, M., & Jingzu, G. (2022). Green organizational culture, organizational performance, green innovation, environmental performance: A mediation-moderation model. Journal of Asia-Pacific Business, 23(2), 161–182. https://doi.org/10.1080/10599231.2022.2072493
[81] J Cohen, P. C. S. W. L. A. (1983). Applied multiple regression. Correl Anal Behav Sci, 2, 255–300.
[82] Jabbari, J., Roll, S., Bufe, S., & Chun, Y. (2022). Cut me some slack! An exploration of slack resources and technology-mediated human capital investments in entrepreneurship. International Journal of Entrepreneurial Behaviour and Research, 28(5), 1310–1346. https://doi.org/10.1108/IJEBR-10-2020-0731
[83] Jackson, R. W., & Ferguson, G. A. (1941). Studies on the reliability of tests. University of Toronto Press.
[84] Jha, S., & Venkatesh, V. (2023). Entrepreneurial satisfaction for women micro-entrepreneurs: A network perspective. Journal of Global Entrepreneurship Research, 13(5), 31–49. https://doi.org/10.1007/s40497-023-00351-7
[85] Johnston, M., Dixon, D., Hart, J., Glidewell, L., Schröder, C., & Pollard, B. (2014). Discriminant content validity: A quantitative methodology for assessing content of theory-based measures, with illustrative applications. British Journal of Health Psychology, 19(2), 240–257. https://doi.org/10.1111/bjhp.12095
[86] Kafetzopoulos, D. (2023). Environmental dynamism and sustainability: The mediating role of innovation, strategic flexibility and HR development. Management Decision, 61(6), 1697–1716. https://doi.org/10.1108/MD-06-2022-0759
[87] Kamolsareeratana, A., & Kouwenberg, R. (2023). Compulsive gambling in the stock market: Evidence from an emerging market. Economies, 11(1). https://doi.org/10.3390/economies11010028
[88] Kaneko, K., & Kajikawa, Y. (2025). Quantitative model of firms' weight using a gravity model in relative coordinates: Case study of photo film industry facing digital innovation. Journal of Informetrics, 19(3), 101676. https://doi.org/10.1016/J.JOI.2025.101676
[89] Kimberly, J. R., & Evanisko, M. J. (1981). Organizational innovation: The influence of individual, organizational, and contextual factors on hospital adoption of technological and administrative innovations. Academy of Management Journal, 24(4), 689–713. https://doi.org/10.2307/256170
[90] Kiran, A., Sri, N. D., Ayyasamy, R. K., Chinnasamy, P., Vellanki, S., & Vujwala, M. (2024). The future of online shopping: Blockchain-powered e-commerce platforms. 2024 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication, 1–6. https://doi.org/10.1109/ICONSCEPT61884.2024.10627920

[91] Koberg, C. S., Detienne, D. R., & Heppard, K. A. (2003). An empirical test of environmental, organizational, and process factors affecting incremental and radical innovation. Journal of High Technology Management Research, 14(1), 21–45. https://doi.org/10.1016/S1047-8310(03)00003-8
[92] Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of E-Collaboration, 11(4), 1–10. https://doi.org/10.4018/IJEC.2015100101
[93] Kohli, R., & Melville, N. P. (2019). Digital innovation: A review and synthesis. Information Systems Journal, 29(1), 200–223. https://doi.org/10.1111/ISJ.12193
[94] Kong, S. C., Cheung, M. Y. W., & Tsang, O. (2024). Developing an artificial intelligence literacy framework: Evaluation of a literacy course for senior secondary students using a project-based learning approach. Computers and Education: Artificial Intelligence, 6. https://doi.org/10.1016/j.caeai.2024.100214
[95] Konopik, J., Jahn, C., Schuster, T., Hoßbach, N., & Pflaum, A. (2022). Mastering the digital transformation through organizational capabilities: A conceptual framework. Digital Business, 2(2). https://doi.org/10.1016/J.DIGBUS.2021.100019
[96] Korucuk, S., Aytekin, A., Ecer, F., Karamaşa, Ç., & Zavadskas, E. K. (2022). Assessing green approaches and digital marketing strategies for twin transition via Fermatean fuzzy SWARA-COPRAS. Axioms, 11(12), 709. https://doi.org/10.3390/AXIOMS11120709
[97] Kowshik, S. T. H., Chew, E. Y. T., & Lee, S. W. H. (2025). Knowledge transfer as a dynamic capability: A meta-analysis of its impact on organizational outcomes in international contexts. Knowledge Management Research & Practice, 1–16. https://doi.org/10.1080/14778238.2025.2519291
[98] Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. International Journal of Information Management, 63, 102466. https://doi.org/10.1016/J.IJINFOMGT.2021.102466
[99] Kristoffersen, E., Blomsma, F., Mikalef, P., & Li, J. (2020). The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies. Journal of Business Research, 120, 241–261. https://doi.org/10.1016/J.JBUSRES.2020.07.044
[100] Kumar, R., Aljuhani, A., Javeed, D., Kumar, P., Islam, S., & Islam, A. K. M. N. (2024). Digital twins-enabled zero touch network: A smart contract and explainable AI integrated cybersecurity framework. Future Generation Computer Systems, 156, 191–205. https://doi.org/10.1016/j.future.2024.02.015
[101] Lee, S.-H., & Workman, J. (2020). How do face consciousness and public self-consciousness affect consumer decision-making? Journal of Open Innovation: Technology, Market, and Complexity, 6(4). https://doi.org/10.3390/joitmc6040144
[102] Liu, H., Choi, C. S., & Kim, K. H. (2024). Roles of value co-creation on social platforms in driving participating businesses' sustainable competitive advantage and performance. Asia Pacific Journal of Marketing and Logistics. https://doi.org/10.1108/APJML-01-2024-0007
[103] Lopes, J., Oliveira, M., Silveira, P., Farinha, L., & Oliveira, J. (2021). Business dynamism and innovation capacity, an entrepreneurship worldwide perspective. Journal of Open Innovation: Technology, Market, and Complexity, 7(1). https://doi.org/10.3390/joitmc7010094
[104] Lynch, T., Ryan, C., Presseau, J., Foster, D. E., Huff, C., Bennett, K., & Cadogan, C. (2024). Development and validation of a theory-based questionnaire examining barriers and facilitators to discontinuing long-term benzodiazepine receptor agonist use. Research in Social and Administrative Pharmacy, 20(2), 163–171. https://doi.org/10.1016/j.sapharm.2023.10.015
[105] MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. MIS Quarterly, 35(2), 293–334. https://doi.org/10.2307/23044045
[106] MacKinnon, D. P., Coxe, S., & Baraldi, A. N. (2012). Guidelines for the investigation of mediating variables in business research. Journal of Business and Psychology, 27(1), 1–14. https://doi.org/10.1007/S10869-011-9248-Z
[107] Maghyereh, A., & Abdoh, H. (2021). Time–frequency quantile dependence between Bitcoin and global equity markets. North American Journal of Economics and Finance, 56. https://doi.org/10.1016/J.NAJEF.2020.101355
[108] Mahakittikun, T., Suntrayuth, S., & Bhatiasevi, V. (2021). The impact of technological-organizational-environmental (TOE) factors on firm performance: Merchant's perspective of mobile payment from Thailand's retail and service firms. Journal of Asia Business Studies, 15(2), 359–383. https://doi.org/10.1108/JABS-01-2020-0012
[109] Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors affecting the organizational adoption of blockchain technology: Extending the technology–organization–environment (TOE) framework in the Australian context. Sustainability, 13(16), 9404. https://doi.org/10.3390/SU13169404
[110] Malope, E. T., van der Poll, J. A., & Ncube, O. (2021). Digitalisation practices in South-African state-owned enterprises: A framework for rapid adoption of digital solutions. Proceedings of the Annual Hawaii International Conference on System Sciences, 2020-January, 4590–4599. https://doi.org/10.24251/HICSS.2021.557
[111] McKinsey. (2023). How Indonesia's ecommerce can drive economic development. https://www.mckinsey.com/featured-insights/asia-pacific/the-digital-archipelago-how-online-commerce-is-driving-indonesias-economic-development
[112] Melović, B., Jocović, M., Dabić, M., Vulić, T. B., & Dudic, B. (2020). The impact of digital transformation and digital marketing on the brand promotion, positioning and electronic business in Montenegro. Technology in Society, 63. https://doi.org/10.1016/j.techsoc.2020.101425
[113] Miao, Y., Li, Y., & Wu, Y. (2024). Digital economy and economic competitive pressure on local governments: Evidence from China. Economic Modelling, 140, 106859. https://doi.org/10.1016/J.ECONMOD.2024.106859
[114] Molina-Castillo, F. J., Meroño-Cerdan, A. L., & López-Nicolás, C. (2020). Impact of business model objectives on marketing innovation activities: A comparison between manufacturing and service firms. European Journal of Innovation Management, 23(1), 177–195. https://doi.org/10.1108/EJIM-12-2018-0259
[115] Moreno, V., Cavazotte, F., & Cesar Valentim Alves, C. (2023). From managerial to organizational dynamic capabilities: Enabling adaptability in turbulent times. Academy of Management Proceedings, 2023(1). https://doi.org/10.5465/AMPROC.2023.15763ABSTRACT
[116] Mottaleb, K. A. (2018). Perception and adoption of a new agricultural technology: Evidence from a developing country. Technology in Society, 55, 126–135. https://doi.org/10.1016/j.techsoc.2018.07.007
[117] Mouazen, A. M., & Hernández-Lara, A. B. (2023). Entrepreneurial ecosystem, gig economy practices and women's entrepreneurship: The case of Lebanon. International Journal of Gender and Entrepreneurship, 15(3), 249–274. https://doi.org/10.1108/IJGE-07-2022-0116
[118] Mughal, M. A., Ullah, A., Yu, X., He, W., Jhanjhi, N. Z., & Ray, S. K. (2024). A secure and privacy preserved data aggregation scheme in IoMT. Heliyon, 10(7), e27177. https://doi.org/10.1016/j.heliyon.2024.e27177
[119] Nadányiová, M., Majerová, J., & Gajanová, Ľ. (2021). Digital marketing, competitive advantage, marketing communication, social media, consumers. Marketing and Management of Innovations, 4, 91–102. https://doi.org/10.21272/mmi.2021.4-08
[120] Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Research Policy, 48(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018
[121] Naskar, S. T., Hota, P. K., & Gupta, V. (2025). The efficiency paradox: How high-performance work systems interact with entrepreneurial orientation in hostile environments to impact firm performance in US firms. International Entrepreneurship and Management Journal, 21(1). https://doi.org/10.1007/S11365-025-01069-6
[122] Nguyen, T. A. (2022). Financial development, human resources, and economic growth in transition countries. Economies, 10(6). https://doi.org/10.3390/economies10060138
[123] Nuseir, M., & Refae, G. A. El. (2022). The effect of digital marketing capabilities on business performance enhancement: Mediating the role of customer relationship management (CRM). International Journal of Data and Network Science, 6(2), 295–304. https://doi.org/10.5267/j.ijdns.2022.1.008
[124] Obiakor, R. T., Uche, E., & Das, N. (2022). Is structural innovativeness a panacea for healthier environments? Evidence from developing countries. Technology in Society, 70. https://doi.org/10.1016/j.techsoc.2022.102033
[125] Oduro, S., De Nisco, A., & Mainolfi, G. (2023). Do digital technologies pay off? A meta-analytic review of the digital technologies/firm performance nexus. Technovation, 128. https://doi.org/10.1016/J.TECHNOVATION.2023.102836
[126] Okorie Awa, H., Ukoha, O., & Emecheta, B. (2012). Integrating TAM and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. Proceedings of the 2012 InSITE Conference, 571–588. https://doi.org/10.28945/1676
[127] Oliveira-Dias, D. de, Maqueira Marín, J. M., & Moyano-Fuentes, J. (2022). Lean and agile supply chain strategies: The role of mature and emerging information technologies. International Journal of Logistics Management, 33(5), 221–243. https://doi.org/10.1108/IJLM-05-2022-0235
[128] Oyewole, O. J., Al-Faryan, M. A. S., Adekoya, O. B., & Oliyide, J. A. (2024). Energy efficiency, financial inclusion, and socio-economic outcomes: Evidence across advanced, emerging, and developing countries. Energy, 289. https://doi.org/10.1016/j.energy.2023.130062
[129] Palacios-Fenech, J., & E, V. (2023). Measuring the adoption and discontinuance of low carbon digitally-enabled innovations: Exploring repeat survey quality. Journal of Cleaner Production, 423, 140311. https://doi.org/10.1016/j.jclepro.2023.140311

[130] Pascucci, F., Savelli, E., & Gistri, G. (2023). How digital technologies reshape marketing: Evidence from a qualitative investigation. Italian Journal of Marketing, 2023, 27–58. https://doi.org/10.1007/s43039-023-00063-6

[131] Pateli, A., Mylonas, N., & Spyrou, A. (2020). Organizational adoption of social media in the hospitality industry: An integrated approach based on DIT and TOE frameworks. Sustainability, 12(17). https://doi.org/10.3390/su12177132

[132] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

[133] Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. Annual Review of Psychology, 63, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

[134] Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. Annual Review of Organizational Psychology and Organizational Behavior, 11, 17–61. https://doi.org/10.1146/ANNUREV-ORGPSYCH-110721-040030

[135] Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

[136] Pueyo-Garrigues, M., Agüera, Z., Andrés, A., Lluch-Canut, M. T., Tricas-Sauras, S., Duaso, M. J., Feliu, A., Pardavila-Belio, M. I., Antón, L., Cornejo-Ovalle, M., Puig-Llobet, M., Moreno-Arroyo, C., Barroso, T., Roca, J., & Martínez, C. (2023). Knowledge, attitudes, behavioral and organizational factors of health professions students for a competent smoking cessation practice: An instrument adaptation and psychometric validation study in Spanish and English samples. Nurse Education in Practice, 70, 103647. https://doi.org/10.1016/j.nepr.2023.103647

[137] Qalati, S. A., Ostic, D., Sulaiman, M. A. B. A., Gopang, A. A., & Khan, A. (2022). Social media and SMEs' performance in developing countries: Effects of technological-organizational-environmental factors on the adoption of social media. SAGE Open, 12(2). https://doi.org/10.1177/21582440221094594

[138] Rahman, M. M., & Hossain, M. E. (2025). Digital dynamics in technology adoption: Exploring socio-economic development through technology and education. Technology in Society, 82, 102906. https://doi.org/10.1016/J.TECHSOC.2025.102906

[139] Rasaputhra, S., Peiris, V., Magallagoda, R., Panditasekara, C., Wisenthige, K., & Jayasuriya, N. (2024). Do technological, environmental and entrepreneurial factors affect social commerce adoption? Journal of Small Business and Enterprise Development, 31(4), 764–785. https://doi.org/10.1108/JSBED-09-2023-0420

[140] Rebiazina, V., Sharko, E., & Berezka, S. (2024). The impact of relationship marketing practices on companies' market and financial performance in emerging markets. Journal of Economics, Finance and Administrative Science, 29(57), 186–204. https://doi.org/10.1108/JEFAS-01-2022-0034/FULL/PDF

[141] Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. International Journal of Research in Marketing, 26(4), 332–344. https://doi.org/10.1016/j.ijresmar.2009.08.001

[142] Ren, Q. (2025). Toward circular economy: Digital-enabled circular economy practices enhancing the European enterprise's performance. Sustainable Development. https://doi.org/10.1002/SD.3517

[143] Rutherford, G. S. W., Hair, J. F., Hair, J. F., Anderson, R. E., & Tatham, R. L. (1979). Multivariate data analysis with readings. Macmillan.

[144] Sahu, G., & Singh, S. (2023). Ecommerce an emerging platform to boost global economy. International Journal For Multidisciplinary Research, 5(1), 1–16. https://doi.org/10.36948/ijfmr.2023.v05i01.1728

[145] Samadbeik, M., Aslani, N., Maleki, M., & Garavand, A. (2023). Acceptance of mobile health in medical sciences students: Applying technology acceptance model. Informatics in Medicine Unlocked, 40, 101290. https://doi.org/10.1016/j.imu.2023.101290

[146] Sanchez, R., & Shibata, T. (2021). Modularity design rules for architecture development: Theory, implementation, and evidence from the development of the Renault–Nissan Alliance "Common Module Family" architecture. Journal of Open Innovation: Technology, Market, and Complexity, 7(4). https://doi.org/10.3390/joitmc7040242

[147] Sarstedt, M. (2008). A review of recent approaches for capturing heterogeneity in partial least squares path modelling. Journal of Modelling in Management, 3(2), 140–161. https://doi.org/10.1108/17465660810890126

[148] Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: indeed a silver bullet"–retrospective observations and recent advances. Journal of Marketing Theory and Practice, 31(3), 261–275. https://doi.org/10.1080/10696679.2022.2056488

[149] Sarstedt, M., Ringle, C. M., Cheah, J. H., Ting, H., Moisescu, O. I., & Radomir, L. (2020). Structural model robustness checks in PLS-SEM. Tourism Economics, 26(4), 531–554. https://doi.org/10.1177/1354816618823921

[150] Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). Long Range Planning, 47(3), 154–160. https://doi.org/10.1016/j.lrp.2014.02.007

[151] Satyro, W. C., Contador, J. C., Gomes, J. A., Monken, S. F. de P., Barbosa, A. P., Bizarrias, F. S., Contador, J. L., Silva, L. S., & Prado, R. G. (2024). Technology-Organization-External-Sustainability (TOES) framework for technology adoption: Critical analysis of models for Industry 4.0 implementation projects. Sustainability, 16(24), 11064. https://doi.org/10.3390/SU162411064

[152] Scaliza, J. A. A., Jugend, D., Chiappetta Jabbour, C. J., Latan, H., Armellini, F., Twigg, D., & Andrade, D. F. (2022). Relationships among organizational culture, open innovation, innovative ecosystems, and performance of firms: Evidence from an emerging economy context. Journal of Business Research, 140, 264–279. https://doi.org/10.1016/J.JBUSRES.2021.10.065

[153] Schamberger, T., Schuberth, F., & Henseler, J. (2023). Confirmatory composite analysis in human development research. International Journal of Behavioral Development, 47(1), 89–100. https://doi.org/10.1177/01650254221117506

[154] Seshadrinathan, S., & Chandra, S. (2021). Exploring factors influencing adoption of blockchain in accounting applications using Technology–Organization–Environment framework. Journal of International Technology and Information Management, 30(1), 30–68. https://doi.org/10.58729/1941-6679.1477

[155] Sharma, A., & Sharma, S. (2024). Adoption of digital marketing in tourism SMEs: A review and research agenda. Management Research Review, 47(7), 1077–1095. https://doi.org/10.1108/MRR-08-2021-0597

[156] Sharma, P. N., Shmueli, G., Sarstedt, M., Danks, N., & Ray, S. (2021). Prediction-oriented model selection in partial least squares path modeling. Decision Sciences, 52(3), 567–607. https://doi.org/10.1111/DECI.12329

[157] Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly, 35(3), 553–572. https://doi.org/10.2307/23042796

[158] [158] Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

[159] Sinulingga, G. (2024). The mediating effect of customer relationship management on trust and satisfaction relationships (Survey of credit card holder customers in Indonesia). Evolutionary Studies in Imaginative Culture, 8(2), 349–357. https://doi.org/10.70082/ESICULTURE.VI.695

[160] Škare, M., & Porada-Rochoń, M. (2020). Multi-channel singular-spectrum analysis of financial cycles in ten developed economies for 1970–2018. Journal of Business Research, 112, 567–575. https://doi.org/10.1016/j.jbusres.2019.10.047

[161] Slomski, V. G., Tavares de Souza Junior, A. V, Lavarda, C. E., Simão Kaveski, I. D., Slomski, V., Frois de Carvalho, R., & Fontes de Souza Vasconcelos, A. L. (2024). Environmental factors, personal factors, and the entrepreneurial intentions of university students from the perspective of the theory of planned behavior: Contributions to a sustainable vision of entrepreneurship in the business area. Sustainability, 16(13). https://doi.org/10.3390/su16135304

[162] Smith, D., Hair, J. F., & Ferguson, K. (2014). An investigation of the effect of family influence on commitment-trust in retailer-vendor strategic partnerships. Journal of Family Business Strategy, 5(3), 252–263. https://doi.org/10.1016/j.jfbs.2013.11.005

[163] Söling, S., Köberlein-Neu, J., Müller, B. S., Dinh, T. S., Muth, C., Pfaff, H., Karbach, U., Kellermann-Mühlhoff, P., Düvel, L., Beckmann, T., Hammerschmidt, R., Jachmich, J., Leicher, E., Brandt, B., Richard, J., Meyer, F., Flume, M., Müller, T., Gerlach, F. M., & Grandt, S. (2020). From sensitization to adoption? A qualitative study of the implementation of a digitally supported intervention for clinical decision making in polypharmacy. Implementation Science, 15(1), 1–12. https://doi.org/10.1186/s13012-020-01043-6

[164] Soomro, B. A., Mangi, S., & Shah, N. (2020). Strategic factors and significance of organizational innovation and organizational learning in organizational performance. European Journal of Innovation Management, 24(2), 481–506. https://doi.org/10.1108/EJIM-05-2019-0114

[165] Stroumpoulis, A., & Kopanaki, E. (2022). Theoretical perspectives on sustainable supply chain management and digital transformation: A literature review and a conceptual framework. Sustainability, 14(8). https://doi.org/10.3390/su14084862

[166] Taherdoost, H., Mohamed, N., & Madanchian, M. (2024). Navigating technology adoption/acceptance models. Procedia Computer Science, 237, 833–840. https://doi.org/10.1016/j.procs.2024.05.172

[167] Tatua, J. (2023). Relationship between firm readiness and the adoption of digitalized marketing operations tactics by chain supermarkets in Kenya. International Journal of Strategic Marketing Practice, 5(1), 1–19. https://doi.org/10.47604/ijsmp.2171
[168] Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. Journal of Management and Organization, 24(3), 359–368. https://doi.org/10.1017/JMO.2017.75
[169] Teece, D. J. (2020). Hand in glove: Open innovation and the dynamic capabilities framework. Strategic Management Review, 1(2), 233–253.
[170] Tian, M., Deng, P., Zhang, Y., & Salmador, M. P. (2018). How does culture influence innovation? A systematic literature review. Management Decision, 56(5), 1088–1107. https://doi.org/10.1108/MD-05-2017-0462
[171] Tornatzky, L., & Fleischer, M. (1990). The process of technology innovation. Lexington Books.
[172] Tornatzky, L. G. (1992). The processes of technological innovation. Technology Transfer, 5–7.
[173] Tornatzky, L. G., Tornatzky, L. G., Fleischer, M., Fleischer, Mitchell., Chakrabarti, A., & Chakrabarti, A. K. (1990). Processes of technological innovation. Lexington Books.
[174] Tracy Francis. (2018, October 12). Generation Z characteristics and its implications for companies. McKinsey. https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/true-gen-generation-z-and-its-implications-for-companies
[175] Tripathi, A., Sardar, S., & Shyam, H. S. (2023). Hybrid crops, income, and food security of smallholder families: Empirical evidence from poor states of India. Technological Forecasting and Social Change, 191, 122532. https://doi.org/10.1016/j.techfore.2023.122532
[176] Troiville, J., Hair, J. F., & Cliquet, G. (2019). Definition, conceptualization and measurement of consumer-based retailer brand equity. Journal of Retailing and Consumer Services, 50, 73–84. https://doi.org/10.1016/j.jretconser.2019.04.022
[177] Umami, Z., & Darma, G. S. (2021). Digital marketing: Engaging consumers with smart digital marketing content. Jurnal Manajemen Dan Kewirausahaan, 23(2), 94–103. https://doi.org/10.9744/jmk.23.2.94-103
[178] Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. MIS Quarterly, 23(2), 239–260. https://doi.org/10.2307/249753
[179] Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. Information Systems Research, 11(4), 342–365. https://doi.org/10.1287/ISRE.11.4.342.11872
[180] [180] Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. Annals of Operations Research, 308(1), 641–652. https://doi.org/10.1007/s10479-021-04049-4
[181] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
[182] Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. Journal of the Academy of Marketing Science, 44(1), 119–134. https://doi.org/10.1007/s11747-015-0455-4
[183] Xie, Y., Desouza, K. C., & Jabbari, M. (2023). On organizational robustness: A conceptual framework. Journal of Contingencies and Crisis Management, 31(1), 105–120. https://doi.org/10.1111/1468-5973.12423
[184] Yang, F., Ren, L., & Gu, C. (2022). A study of college students' intention to use metaverse technology for basketball learning based on UTAUT2. Heliyon, 8(9). https://doi.org/10.1016/j.heliyon.2022.e10562
[185] Yin, R. K. (2013). Validity and generalization in future case study evaluations. Evaluation, 19(3), 321–332. https://doi.org/10.1177/1356389013497081
[186] Zaman, S. A. A., Vilkas, M., Zaman, S. I., & Jamil, S. (2024). Digital technologies and digitalization performance: The mediating role of digitalization management. Journal of Manufacturing Technology Management. https://doi.org/10.1108/JMTM-04-2024-0176
[187] Zhang, B., Ying, L., Khan, M. A., Ali, M., Barykin, S., & Jahanzeb, A. (2023). Sustainable digital marketing: Factors of adoption of M-technologies by older adults in the Chinese market. Sustainability, 15(3). https://doi.org/10.3390/su15031972
[188] Zhang, F., & Zhu, L. (2019). Enhancing corporate sustainable development: Stakeholder pressures, organizational learning, and green innovation. Business Strategy and the Environment, 28(6), 1012–1026. https://doi.org/10.1002/BSE.2298
[189] Zhang, M., Cheng, R., Fei, J., & Khanal, R. (2024). Enhancing digital innovation ecosystem resilience through the interplay of organizational, technological, and environmental factors: A study of 31 provinces in China using NCA and fsQCA. Sustainability, 16(5). https://doi.org/10.3390/su16051946
[190] Zhao, J., Wang, X., Yao, X., & Xi, X. (2024). Digital-intelligence transformation, for better or worse? The roles of pace, scope and rhythm. Internet Research. https://doi.org/10.1108/INTR-12-2023-1125
[191] Zhao, R., Hou, W., Kumar, V., & Kumar, A. (2023). Signalling effects of doing good in global ICO markets. Journal of Business Research, 168. https://doi.org/10.1016/j.jbusres.2023.114224
[192] Zhou, C., Li, H., Zhang, L., & Ren, Y. (2023). Optimal recommendation strategies for AI-powered e-commerce platforms: A study of duopoly manufacturers and market competition. Journal of Theoretical and Applied Electronic Commerce Research, 18(2), 1086–1106. https://doi.org/10.3390/jtaer18020055#