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Research Article

Empirical Evidence of The Moderating Role of Firm Strategic Types Between New-Age Technology Adoption Intensity and Its Antecedents: A Study on Startups

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Abstract: This study investigates how startups adopt new-age technologies (NATs) and how their strategic orientation influences this process. Drawing on the Technology-Organization-Environment (TOE) framework, Institutional Theory, and the Resource-Based View (RBV), the paper examines four antecedents - technological opportunism, top management support, negative normative pressure and positive normative pressures, and their effect on NAT adoption intensity. Using survey data from 226 Indian startups and multi-group structural equation modeling, the study finds that strategic firm types significantly moderate these relationships. Results show that prospectors adopt NATs more intensively due to proactive leadership and alignment with external expectations, while reactors are influenced primarily by external pressures. The study highlights that technology adoption is not uniform across startups. Adoption outcomes depend on a firm's strategic posture and its ability to respond to both internal and external drivers. These insights contribute to a better understanding of potentially disruptive technologies in resource-constrained, high-growth environments.

Keywords: New-age technologies; Disruptive innovations: Startups; Technology adoption intensity; TOE framework; Strategic orientation; Normative pressure; Structural equation modeling..

INTRODUCTION

In today's fast-evolving business environment, survival and growth are increasingly difficult, particularly for startups. Startups operate under significant constraints yet face the challenge to adapt swiftly to ongoing technological disruptions. The rise of new-age technologies (NATs) has transformed how markets function, creating both unprecedented opportunities and complex challenges. These technologies are potentially disruptive, characterized by rapid innovation cycles and substantial uncertainty regarding their societal and commercial impact. For startups, these technologies can offer a competitive edge, but also carry risks due to their complexity and evolving nature.

The question then arises: how do startups, which are resource-constrained yet agile, navigate the adoption of these disruptive technologies? While extant literature has studied the adoption of individual technologies such as AI or blockchain, very few studies have addressed the broader category of NATs, especially among startups. The marketing literature has generally concentrated on individual-level adoption (e.g., consumers or employees), with limited emphasis on the organizational adoption of potentially radical and disruptive technologies.

Parthasarathy and Sohi (1997) introduced the idea of "dual adoption", first at the organizational level, followed by individual adoption. For NATs that are typically emergent and unstable in their maturity, focusing on organizational-level adoption, particularly within startups, is both timely and critical. Recent studies on organizational-level adoption show that NATs like AI, IoT, blockchain, and machine learning are changing how organisations create value and connect with customers (Kumar et al., 2021). Kumar stresses that success depends not just on adopting the technology but on aligning it with the company's strategy and readiness.

Chen (2022) adds that AI, in particular, doesn't just automate work, it boosts what firms can already do. Chen assesses the antecedents like technological opportunism, customer orientation, normative pressure and top management support in the context of the intensity of AI adoption, calling for the assessment of such antecedents in the broader context of NATs. For startups, NATs like AI can multiply their limited resources by helping with faster decisions and smarter operations. However, the impact still varies depending on the firm's strategic direction and how deeply they adopt the technology. These insights strengthen the case for studying how different strategic types among startups influence the link between adoption drivers and how intensely they use new technologies.

LITERATURE REVIEW

This study draws upon three foundational theoretical perspectives: the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), Institutional Theory (Scott, 1987), and the Resource-Based View (RBV) of the firm (Wernerfelt, 1984). According to

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the TOE framework, the adoption of technological innovations is influenced by three dimensions: the technological context (including internal and external technologies), the organizational context (resources and structure), and the environmental context (including competitive pressure and regulation).

Institutional theory emphasizes the role of external pressures—such as competitors, customers, and regulators—in shaping organizational behavior. These institutional forces often guide firms toward isomorphism, leading them to emulate the practices of industry leaders (Awa, Ojiabo, & Emecheta, 2015). RBV complements these perspectives by focusing on how firm-specific capabilities enable the recognition and exploitation of technological opportunities.

Although these frameworks have been widely applied to traditional IT adoption (Teo, Ranganathan, & Dhaliwal, 2006), their application to the adoption intensity of new-age technologies by startups remains underexplored.

Conceptual/Theoretical Framework

In light of the TOE, Institutional Theory, and RBV frameworks, we examine the influence of four antecedents: technological opportunism, top management support, negative normative pressure, and positive normative pressure.

Technological Opportunism

Technological opportunism refers to a firm's capability to sense and respond to technological changes in its environment (Srinivasan, Lilien, & Rangaswamy, 2002). It comprises two dimensions: technological-sensing and technological-responding capabilities (Chen & Lien, 2013; Sarkees, 2011). For startups, which often lack formal R&D structures, the ability to opportunistically leverage emerging technologies can become a core differentiator. RBV suggests that such dynamic capabilities are rare and difficult to imitate, giving startups with strong technological opportunism a competitive edge. Therefore:
H1: Technological opportunism is positively related to the intensity of new-age technology adoption by startups.

Top Management Support

Top management's strategic vision and commitment to innovation play a critical role in the adoption of radical technologies (Shao, Feng & Hu, 2016). Particularly in startups, where leadership is often synonymous with ownership, top management's emphasis on technological transformation can catalyze adoption intensity. The TOE framework states that managerial support facilitates cross-functional alignment, reduces resistance to change, and secures necessary resources for implementation (Kohli & Jaworski, 1990). Hence:

H2: Top management support is positively related to the intensity of new-age technology adoption by startups.

Negative Normative Pressure

Negative normative pressure refers to the social disapproval or ethical resistance that discourages startups from adopting certain emerging technologies. Unlike positive norms that promote conformity, negative norms reflect societal concerns—such as environmental harm, data misuse, or ethical risks—that signal reputational or legitimacy threats if adoption proceeds. Startups, being legitimacy-seeking and resource-constrained, are especially cautious in environments where public sentiment or stakeholder narratives portray a technology as irresponsible or controversial (Chatterjee et al., 2021; Liang et al., 2021).

Rooted in institutional theory, this form of pressure inhibits rather than enables adoption. Startups may avoid technologies like facial recognition, energy-intensive blockchain, or XR perceived as invasive or unsustainable, not due to capability gaps but to avoid backlash, customer distrust, or regulatory scrutiny (Scott, 2014; Jöhnk et al., 2021).

H3: Negative normative pressure is negatively related to the intensity of new-age technology adoption by startups.

Positive Normative Pressure

Positive normative pressure reflects the influence of social expectations that encourage startups to adopt emerging technologies viewed as legitimate, modern, or strategically necessary. This pressure originates from industry peers, investors, professional networks, or innovation ecosystems that endorse the adoption of technologies such as ethical AI, green cloud computing, or blockchain for transparency (Teo et al., 2003; DiMaggio & Powell, 1983). For startups, aligning with these norms helps signal credibility, enhance reputation, and access resource networks.

Institutional theory suggests that organizations conform to such norms to gain legitimacy and social acceptance (Scott, 2014). Startups, often striving for visibility and market entry, are particularly sensitive to normative cues that confer approval and reduce perceived innovation risk (Teo et al., 2003).

H4: Positive normative pressure is positively related to the intensity of new-age technology adoption by startups.

Moderating Role: Strategic Types

Following the Miles and Snow (1978) strategic typology, startups can be categorized as prospectors, analyzers, defenders, and reactors. Prospectors actively seek new opportunities and are more inclined to adopt disruptive technologies. In contrast, defenders focus on stability, and reactors respond only under threats.

We propose that the strategic type moderates the relationship between the antecedents and adoption intensity:

H5: The positive relationship between (a) technological opportunism, (b) top management support, (c) negative normative pressure, and (d) positive normative pressure and new-age technology adoption intensity will be strongest for prospectors, followed by analyzers, defenders, and reactors. The conceptual framework is shown in figure

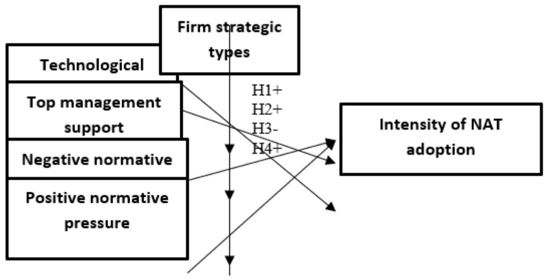

Figure 1: Conceptual framework

RESEARCH METHODOLOGY

To empirically evaluate the hypotheses formulated, an online survey method was employed. This approach was deemed most appropriate as it allows for the integration of insights from startup founders and senior managers with firsthand knowledge of new-age technologies (NATs). The survey format was specifically chosen for its advantages: it ensures respondent anonymity, thereby enhancing data authenticity; it is efficient in terms of time and resource utilization; and it provides respondents the flexibility to complete the questionnaire at their convenience, which is especially pertinent in the fast-paced startup ecosystem.

In line with the research objective focusing on New-Age Technology (NAT) adoption within startups, several prominent national-level startup events, including *Startup Mahakumbh*, were strategically targeted for participant recruitment. Founding team members were selected as primary informants given their dual roles in strategic planning and operational decision-making within their organizations. Their comprehensive understanding of both the strategic and technological aspects of the business made their insights particularly valuable. Based on initial outreach, the study anticipated receiving approximately 280 valid responses from startup founders, forming a robust dataset for empirical analysis.

All measurement items used in the survey were adapted from well-established scales. To contextualize these scales within the NAT domain, a preliminary qualitative phase was conducted. This involved in-depth interviews with two senior executives from a leading NAT-driven startup, who reviewed the research design and provided feedback on questionnaire relevance and clarity. Following their input, two marketing academics reviewed the revised instrument to further refine question wording and format. A pilot test was subsequently conducted, involving 252 participants. After implementing two attention-check questions to ensure data quality, 32 complete and valid responses were retained for analysis.

The pilot test aimed to validate item clarity and scale reliability. Exploratory Factor Analysis (EFA) guided refinements, with items showing weak or cross-factor loadings either modified or removed. Additional items were introduced to ensure a minimum of three indicators per construct, in line with recommendations by Churchill (1979).

Post data collection, rigorous data cleaning procedures were employed. Response behavior was examined for straight-lining and rapid completion ("speeding"), which often indicate inattentiveness. Two mechanisms were used to detect these issues: response time tracking, as supported by Brown, Suter, and Churchill (2013) and Clow and James (2013), and embedded attention checks. Respondents were asked to follow explicit instructions (e.g., "Please choose option 2") and to express their level of agreement with a widely accepted statement ("Making profit is important to a firm"). Only those passing these checks were included in the final analysis. Additionally, responses with excessive missing data were excluded.

The analysis proceeded in a structured seven-stage process using SPSS 25.0 and AMOS 25. Initially, assumption tests were conducted to assess the data's normality and suitability for regression. Descriptive statistics indicated acceptable skewness (-1.1 to 1.1) and kurtosis (within ±2.0), confirming the appropriateness of the data for parametric testing. A descriptive overview of respondents' demographic profiles and professional experiences followed, using frequencies, percentages, means, and standard deviations.

EFA was applied to examine the dimensionality and internal consistency of the constructs, which included technological opportunism, top management emphasis, negative normative pressure, positive normative pressure, firm strategic types, and intensity of NAT adoption. A factor loading threshold of 0.5 and eigenvalue >1 were applied, and Cronbach's alpha was used to assess reliability. Subsequently, Confirmatory Factor Analysis (CFA) tested the measurement model's validity. Indicators of model fit included RMSEA, TLI, GFI, AGFI, PNFI, and CFI, as recommended by Fornell and Larcker (1981), with the analysis conducted using AMOS 23.

To address potential common method variance (CMV), a subset of the social desirability scale was used, including items measuring socially sensitive tendencies (e.g., envy, self-doubt). Correlation analyses showed that CMV was minimal, with only technological opportunism showing a weak association. A CMV latent construct was also included in the SEM model, and parameter shifts remained below 0.2, indicating limited bias (MacKenzie & Podsakoff, 2012).

Finally, Structural Equation Modeling (SEM) was utilized to test the full model, estimating all direct and indirect effects simultaneously. To assess the moderating role of firm strategic types, a multi-group SEM approach was adopted. This allowed for comparison of model fit and path differences across strategic typologies, providing robust insights into the conditional relationships at play in NAT adoption among startups.

RESULTS

The study surveyed a total of 226 startup representatives. Among them, 63.6% were male and 36.4% were female, indicating a slightly male-dominated respondent base. Educationally, a large proportion held college degrees (62.7%) or master's degrees

(53.1%), reflecting a well-educated sample. On average, respondents had 3.88 years of experience working in a founder's office and 3.43 years within their respective industries. These metrics indicate that participants were sufficiently knowledgeable to contribute meaningfully to the study.

Exploratory Factor Analysis

The suitability of the data for factor analysis was established through key statistical indicators. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.873, which is considered meritorious (Kaiser, 1974). The communalities ranged from 0.681 to 0.712, with an average above 0.694, indicating that a substantial portion of variance was explained by the extracted factors. Bartlett's Test of Sphericity was also significant ($\chi^2 = 1900.433$, df = 136, $p < .001$), further supporting the appropriateness of the factor model.

Principal Component Analysis (PCA) with varimax rotation revealed clean factor structures, with all retained items demonstrating factor loadings above 0.50. Only components with eigenvalues greater than 1 were retained. This step helped mitigate multicollinearity and improved the robustness of the measurement model (Bollen, 1989).

Table 1: Factor loading and items

Variable	Factor loading	α
1. Technological opportunism		.848
TO1	0.861	
TO2	0.835	
TO3	0.798	
TO4	0.775	
2. Top management emphasis		.844
TME1	0.769	
TME2	0.766	
TME3	0.737	
TME4	0.727	
3. Negative Normative Pressure		.849
CO1	0.854	
CO2	0.818	
CO3	0.816	
CO4	0.741	
CO5	0.615	
4. Positive Normative Pressure		.831
NP1	0.785	
NP2	0.774	
NP3	0.766	
NP4	0.677	
6. The intensity of NAT adoption		.900
AI1	0.893	
AI2	0.891	
AI3	0.865	

Reliability Test

Internal consistency was assessed using Cronbach's alpha. The results indicate strong reliability across all constructs: Technological Opportunism (α = .851), Top Management Emphasis (α = .846), Negative Normative Pressure (α = .851), Positive Normative Pressure (α = .833), and Intensity of New-Age Technology (NAT) Adoption (α = .903). All values exceed the widely accepted threshold of 0.70 (Nunnally, 1967), confirming the internal coherence of the measurement scales.

Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was performed using AMOS 25 to validate the proposed measurement model. Items with loadings below 0.50 were excluded. Model fit indices were acceptable: $\chi^2 = 1962.281$, RMSEA = 0.077, CFI = 0.826, and NFI = 0.832. These results confirm the adequacy of the measurement model.

Hu and Bentler (1999) suggested that a CFI ≥ .90 and RMSEA ≤ .10 indicate acceptable model fit. The model in this study approaches these standards and is thus deemed acceptable for further analysis.

Table 2: Standardized Measurement Coefficients and t-Values Resulting from CFA

Variable	**Standardized loading**	**t-values**	**AVE**	**CR**
1. Technological opportunism			**.597**	**.852**
TO1	0.717			
TO2	0.879	11.45		
TO3	0.768	10.52		
TO4	0.715	9.82		
2. Top Management Support			.584	.846
TME1	0.803			
TME2	0.794	12.04		
TME3	0.731	10.97		
TME4	0.726	10.91		
3. Negative Normative Pressure			.545	.853
CO1	0.59			
CO2	0.708	8.07		
CO3	0.814	8.76		
CO4	0.765	8.49		
CO5	0.796	8.64		
4. Positive Normative Pressure			**.569**	**.837**
NP1	.786			
NP2	.780	12.69		
NP3	.771	11.23		
NP4	.676	9.49		
6. The intensity of NAT adoption				
AI1	.735	11.15	.556	.791
AI2	.765	10.67		
AI3	.736			

Content Validity

To ensure comprehensive measurement coverage, content validity was established through a literature review and a pilot study. Experts were consulted to assess the clarity and relevance of the items, ensuring that each scale accurately captured its intended construct.

Convergent Validity

Following Fornell and Larcker's (1981) approach, convergent validity was confirmed as all constructs displayed composite reliabilities above 0.70 and Average Variance Extracted (AVE) values above 0.50. All item loadings were statistically significant, confirming that the indicators meaningfully represented their respective latent constructs.

Discriminant Validity

Discriminant validity was demonstrated through the Fornell-Larcker criterion. The square root of each construct's AVE exceeded its correlations with other constructs, verifying that each measure captured a distinct concept. This supports the overall construct validity of the instrument.

Structural Equation Modeling – Moderation Effects

To test the moderating role of firm strategic types, multi-group structural equation modeling (SEM) was used. Firms were classified into prospector, analyzer, defender, or reactor categories based on dominant response patterns to five strategic orientation items. Where responses were ambiguous, additional qualitative assessment was applied.

Of the 226 firms, 45 were classified as prospectors, 12 as analyzers, 36 as defenders, and 23 as reactors. These groups formed the basis for the moderation analysis, which proceeded in two stages using multi-group SEM techniques. The specific results are shown in table 3:

Table 3: Hypotheses and Structural Paths

Hypothesized Paths	Hypothesis	Standardized Coefficients	t-value	Assessment ($p < .05$)
Technological opportunism → intensity of NAT adoption	H1+	-0.30	-.521	Not supported
Top management emphasis→ intensity of NAT adoption	H2+	.604***	8.022	Supported
Negative normative pressure → intensity of NAT adoption	H3-	.280***	4.284	Supported
Positive normative pressure→ intensity of NAT adoption	H4+	.356***	5.615	Supported
Moderation effects				
Technological opportunism → intensity of NAT adoption (prospector)	H5a	-0.137	-1.653	.098 (non-significant)
Technological opportunism → intensity of NAT adoption (analyzer)		-0.052	-0.783	.435 (non-significant)
Technological opportunism → intensity of NAT adoption (defender)		0.095	0.677	.498 (non-significant)
Technological opportunism → intensity of NAT adoption (reactor)		0.011	0.058	.954 (non-significant)
Top management emphasis → intensity of NAT adoption (prospector)	H5b	0.278	2.308	.021 (significant)
Top management emphasis → intensity of NAT adoption (analyzer)		0.538	5.362	*** (significant)
Top management emphasis → intensity of NAT adoption (defender)		0.632	4.129	*** (significant)
Top management emphasis → intensity of NAT adoption (reactor)		0.094	0.532	.594 (non-significant)
Negative normative pressure → intensity of NAT adoption (prospector)	H5c	0.388	3.091	.003 (significant)
Negative normative pressure → intensity of NAT adoption (analyzer)		-0.050	-0.639	.524 (non-significant)
Negative normative pressure → intensity of NAT adoption (defender)		-0.089	-0.828	.407 (non-significant)
Negative normative pressure → intensity of NAT adoption (reactor)		0.008	0.041	.967 (non-significant)
Positive normative pressure → intensity of NAT adoption (prospector)	H5d	0.586	5.971	<.01 (significant)

Positive normative pressure → intensity of NAT adoption (analyzer)		0.342	3.432	*** (significant)
Positive normative pressure → intensity of NAT adoption (defender)		0.559	3.443	*** (significant)
Positive normative pressure → intensity of NAT adoption (reactor)		0.849	3.296	*** (significant)
Notes: N= 226, χ2= 322.540, df = 104, CFI = .857, TLI = .684, and RMSEA = .096 * *p*<.1, ** *p*<.05; *** *p*<.01, † non-significant				

DISCUSSION

This study set out to explore some of the antecedents of NATs adoption intensity by startups and how these adoption patterns are influenced by firm-level strategic orientation. Our empirical findings demonstrate that top management emphasis, negative normative pressure, and positive normative pressure are key antecedents influencing the intensity of NAT adoption across startups. Crucially, these effects are moderated by the strategic type of the firm—prospector, analyzer, defender, or reactor—underscoring the need to contextualize adoption behavior within the firm's broader strategic posture.

Prospector-type startups, which are characterized by innovation-seeking and experimentation, exhibited the highest intensity of NAT adoption. They were most responsive to internal cues such as leadership prioritization, as well as external pressures like market competition and peer behavior. Analyzer and defender firms demonstrated moderate levels of adoption, showing sensitivity primarily to structured managerial support and perceived industry norms. In contrast, reactor-type firms, typically reactive and lacking a clear strategic framework, were largely influenced only by normative pressures, particularly negative ones. This suggests that such firms tend to adopt NATs more as a response to external threats or fear of obsolescence than through proactive internal strategies.

Theoretical Implications

This study contributes to the literature on technology management and strategic entrepreneurship by examining how different types of startups interpret and respond to the antecedents of New-Age Technology (NAT) adoption. Grounded in the dynamic capabilities view (Teece et al., 1997), our findings support the argument that a firm's strategic orientation plays a significant role in shaping its ability to sense, seize, and transform in response to technological opportunities and pressures.

Unlike traditional models that treat technology adoption as a largely homogeneous decision-making process, this research highlights the heterogeneity of startup behavior. By incorporating the Miles and Snow (1978) typology of strategic orientations, we uncover how the same antecedents can result in different levels of adoption intensity depending on the firm's internal strategy. For example, while top management support was a strong predictor of NAT adoption across most types, its impact was most pronounced in prospector firms that are structurally and culturally aligned with exploratory initiatives.

Additionally, this study refines existing technology adoption theories by integrating both internal (e.g., leadership emphasis) and external (e.g., normative pressure) antecedents, and examining how their influence is moderated by strategic posture. This multidimensional perspective helps move beyond linear models of adoption and suggests a more nuanced, interaction-based framework.

Finally, by focusing on startups in an emerging economy context (India), the study addresses an important gap in the literature, where most empirical studies have traditionally concentrated on large firms or developed markets. In doing so, it broadens the theoretical understanding of how strategic behavior and institutional contexts jointly shape technological evolution in entrepreneurial ecosystems.

Managerial Implications

The findings of this study offer valuable guidance for startup founders, executives, and policy-makers aiming to drive the adoption of New-Age Technologies (NATs) within emerging innovation ecosystems. One of the most important takeaways is that NAT adoption is not merely a question of access to technology or awareness of trends, it is heavily influenced by strategic orientation and leadership intent.

First, the consistent significance of top management support across most strategic types, especially among prospectors and analyzers, highlights the central role of leadership in driving digital transformation. For prospector-type startups in particular, investment in experimentation and pilot programs can accelerate early adoption and help maintain a competitive edge.

Second, the results underscore the impact of normative pressures, especially in influencing reactive or conservative firms. Startups categorized as reactors were least likely to adopt NATs on their own initiative but responded strongly to perceived expectations from industry stakeholders, competitors, and customers. This suggests that policy-makers, incubators, and startup networks can amplify NAT adoption by shaping clear industry benchmarks, showcasing peer success stories, and normalizing technology adoption as a standard business practice.

Third, the study reveals that technological opportunism, although often celebrated in entrepreneurial discourse, had a comparatively lower influence on NAT adoption. This implies that simply being open to innovation is insufficient. Firms need concrete capabilities and managerial commitment to act on those opportunities. Therefore, startups should invest not only in scanning for new technologies but also in developing internal routines, upskilling talent, and clarifying execution strategies.

Lastly, understanding a firm's strategic posture can help tailor adoption strategies. For example: (a) Prospectors thrive when given autonomy, funding, and experimental space, (b) Analyzers benefit from clear performance metrics and structured rollouts, (c) Defenders may need reassurance through ROI modeling and risk mitigation, and (d) Reactors often require external nudges—compliance standards or competitive shocks—to catalyze action. In essence, a one-size-fits-all approach to NAT adoption is unlikely to succeed. Instead, startup leaders should assess their firm's strategic orientation and design technology integration strategies that align with both their internal culture and external demands.

Limitations and Future Research Directions

First, the cross-sectional design limits the ability to assess changes over time. Future studies could adopt a longitudinal approach to better understand how NAT adoption evolves across different stages of startup growth. Second, the research is confined to Indian startups. Although this offers context-specific insights, the findings may not be directly generalizable to other countries or regions. Comparative studies across diverse ecosystems could enrich our understanding of how institutional and cultural factors affect NAT adoption.

Third, the study focuses on a core set of antecedents. Future research could explore additional factors such as organizational culture, funding environment, or customer readiness, which may also influence adoption decisions. Lastly, while this study treats NAT adoption broadly, future research could examine adoption patterns across specific categories of technologies (e.g.,security-oriented technologies and data-oriented technologies) to uncover differentiated drivers and barriers.

CONCLUSION

This paper studies the complex interplay between firm strategy and technological responsiveness. While the external environment plays a critical role in shaping NAT adoption, the firm's internal orientation determines how these signals are interpreted and acted upon. By mapping adoption behavior onto strategic types, this study offers a more granular and realistic model of new-age technology diffusion in startup ecosystems.

Findings demonstrate that adoption is not solely a function of technological readiness or managerial intent, but also of the firm’s underlying strategic orientation. While top management support and normative pressures consistently influence adoption, their strength and direction vary significantly across strategic types. Prospectors exhibit the highest responsiveness to both internal drivers and external cues, while reactors remain largely passive unless compelled by strong normative forces.

This research contributes to the literature by showing that the strategic context of the firm is not merely a background variable but a critical mechanism shaping the adoption trajectory of potentially disruptive technologies. It calls for a shift from one-size-fits-all adoption models toward more contingent, strategy-aware frameworks, and opens up various research questions in the field of strategic entrepreneurship.

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