

Unlocking Digital Entrepreneurial Behavior: The Role of Ecosystem Support, Intention, and Innovation

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Abstract

As the economy becomes more digitalized, it is critical to understand the determinants of digital entrepreneurship behavior (DEB) for entrepreneurial ecosystems and policy frameworks. In particular, this study examines the mediating effects of entrepreneurial intention (EINT) and entrepreneurial innovation (EINN), and the moderating effect of entrepreneurial education (EE) on the relationship between ecosystem support and DEB. Based on Institutional Theory, the Theory of Planned Behavior (TPB), and Innovation Diffusion Theory (IDT), the study conducted a structured survey on 343 digital entrepreneurs in India and used a Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data. Findings show that ecosystem support has a significant direct and indirect (EINT and EINN) effect on DEB. Although EE has a significant direct impact on DEB, the moderating role is not significant, implying that informal and experiential learning could be more potent than traditional interventions. The results contribute to theoretical discussion by linking ecosystemic and behavioral levels of analysis of digital entrepreneurship, and provide practical implications for educators, incubators and policymakers in the context of supporting digital entrepreneurship ventures in emerging markets.

Keywords

Digital entrepreneurial behavior, entrepreneurial ecosystem, entrepreneurial intention, innovation capability, entrepreneurial education

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Introduction

In the fast-digitalizing world, Digital Entrepreneurial Behavior (DEB) has become a critical force for innovation, economic vibrancy and employment in international economies. Unlike conventional entrepreneurial behavior, DEB demonstrates how entrepreneurs are able to use digital tools, platforms and ecosystems to recognize opportunities, innovate and scale ventures. It is therefore imperative to drive a better understanding of what influences DEBs, notably in settings such as those where digital transformation is redefining business models and entrepreneurial processes (Essén et al., 2022; Kreuzer et al., 2022).

Although the individual-level characteristics have frequently been analyzed in the entrepreneurship domain (e.g., risk propensity and opportunity recognition), the increasing role of external digital ecosystems in shaping this new venture formation requires an innovative focus (Jang & Lee, 2025). The role of the Digital Entrepreneurial Ecosystem (DEE)—consisting of digital infrastructure, financial support, market endowments and institutional environments—is critical for entrepreneurs to come to action and to navigate and succeed in digital markets (Satalkina & Steiner, 2020). Recent research has also highlighted the significance of agile policy systems, platform governance, and entrepreneurial culture in shaping digital startup outcomes (Griva et al., 2021).

Despite the growing interest in entrepreneurship, it remains unclear how ecosystem-level determinants are exactly translated into digital entrepreneurial action. Most previous research has focused on either ecosystem inputs or individual motivations, leaving largely unaddressed the question of how ecosystems influence behavior in an integrative way (Guerrero et al., 2020; Wurth et al., 2021). This is, theoretically and empirically, a gap.

The potential explanation lies in the cognitive mechanisms that bridge environmental support and entrepreneurial behavior. Entrepreneurial Intention (EINT), derived from the Theory of Planned Behavior (TPB) (Ajzen, 1991), is widely recognized as a precursor to entrepreneurial action. However, in the context of the fast-moving digital space, intention may not be enough—capability-based mechanisms, such as innovation, can significantly supplement and bridge ecosystem support to behavior (Dwivedi et al., 2021).

This introduces the role of Entrepreneurial Innovation (EINN)—a dynamic capability that allows entrepreneurs to respond to change, experiment with digital business models, and stay competitive (Sahebalzamani et al., 2022). Innovation capability may mediate the DEE–DEB relationship by equipping entrepreneurs to reconfigure and deploy resources effectively, yet its influence remains underexplored in empirical models.

In addition, Entrepreneurial Education (EE) is a critical enabler of entrepreneurial outcomes, but the moderating role of EE in digital dimensions remains unclear. In a world where dynamism, exploration, and access to knowledge are

more important than formal training, it is vital to understand whether EE exponentially enhances the DEE–DEB relationship—or if, under specific conditions, it might dilute the relationship.

Building on the foregoing discussion, this article aims to examine the effects of DEE on DEB in the context of both old and new ecosystem environments, both directly and indirectly. Based on Entrepreneurial Ecosystems Theory, the TPB, and Dynamic Capabilities Theory, the study presents an integrated framework that complements the interaction among environmental, cognitive, and capability dimensions from a digital entrepreneurship perspective.

This article makes three main contributions to digital entrepreneurship. First, it clarifies how ecosystem support influences entrepreneurial actions through intention and innovation, highlighting the mechanisms at the micro and macro levels. Second, it examines how EE moderates this relationship, addressing boundary conditions that affect outcomes. Third, by integrating Entrepreneurial Ecosystems Theory, the TPB, and Dynamic Capabilities, it offers a comprehensive framework linking environmental, cognitive, and capability factors. Practically, it provides insights for ecosystem builders, educators, and policymakers on how digital infrastructure, support, and education impact DEB.

Theoretical Background and Hypothesis Development

Theoretical Background

This section provides a theoretical foundation for the research, organized according to the main variables in the research model. Each dimension—DEB, DEE, EINT, EINN and EE—is treated in accordance with the theoretical premise. This model is the amalgam of the Entrepreneurial Ecosystem Theory, the TPB and the Dynamic Capabilities Theory.

Digital Entrepreneurial Behavior

DEB is characterized as the way entrepreneurs find, set up and grow businesses in digitally mediated markets. These include e-commerce, new technologies, online markets, and data analytics for strategy (Salhie & Al-Abdallat, 2021).

DEB, in the context of this study as a dependent variable, is defined as the entrepreneurial tendency that results from digital competence and environmental supports. The DEB is not only considered as an opportunity (Foss et al., 2013) but also as pervasive external ecosystem-level influences (Elia et al., 2019), and internal cognitive-level antecedents (Maroufkhani et al., 2022). It is the digital entrepreneurship way to react to the dynamic digital habitats.

Digital Entrepreneurial Ecosystem

The DEE is a complex mix of digital infrastructure, institutions, policy environment and enablers that specifically support digital entrepreneurship. It is made up of an asset mix including platforms, Fintech services, cloud technology, funding ecosystem and regulations specifically designed for digital companies (Antonizzi & Smuts, 2020)

DEE is grounded in Entrepreneurial Ecosystem Theory (Isenberg, 2011) that emphasizes the significance of external context in influencing entrepreneurial outcomes. DEE is the extrapolation of those theories and results to technology-intensive settings. DEE operates at two levels: the level of development of entrepreneurial intent and the level of actual behavior change via the elimination of constraints and creation of opportunities (Clark et al., 2020).

This research considers DEE as the principal predictor. It is posited to have an impact on DEB indirectly (through psychological and capability-based mechanisms) and also directly.

Entrepreneurial Intention

EINT refers to an individual's cognitive state to kick-start a venture. It reflects dedication, goal-direction and proactivity (Kong et al., 2020)

The theoretical foundations of EINT are built on the TPB (Ajzen, 1991), which posits that intention is the immediate precursor to behavior. They operationalize it as a function of attitude, subjective norm and perceived behavioral control, which are all regarded as functions of the supportiveness of the surrounding ecosystem.

EINT is proposed as a mediator when describing the DEE–DEB relationship. Consistent with prior research, the supporting ecosystem enhances entrepreneurial self-efficacy and desirability, which also influences the intention (Farrukh et al., 2022; Liñán & Fayolle, 2015). According to the model, intention is the psychological link between the ecosystem and behavior.

Entrepreneurial Innovation

EINN is the entrepreneurs' and organizations' capacity to develop and validate new business models. The reallocation of resources enables entrepreneurs to respond to changing customer preferences (Siaw & Sarpong, 2021)

EINN draws from the Dynamic Capabilities Theory, which posits that a firm's capability to recognize and exploit environmental opportunities as well as to reconfigure these capabilities in response to environmental changes is the source of value creation (Kim & Yang, 2024). In the context of digital entrepreneurship, this capability results in entrepreneurs' agility to swiftly produce and scale innovations in response to environmental changes.

In the current research, EINN is conceptualized as the second mediator linking DEE and DEB. While EINT indicates the cognition in decision-making, EINN represents the strategic ability to take action. Collectively, they offer a two-lens reply to how ecosystem resources influence entrepreneurial action.

Entrepreneurial Education

The notion of EE refers to formal and informal learning experiences that engender knowledge, skills and competences related to entrepreneurship. This includes formally structured courses, incubation training, online classes and learning by doing (Clark et al., 2020).

EE is treated as a moderator in the DEE–DEB relationship. It either enhances or diminishes the effect that ecosystem support has on entrepreneurial behavior. This notion is conceptually consistent with human capital and institutional

perspectives to the extent that education is a loudspeaker of entrepreneurial activity (Sedeh et al., 2021).

The moderating effect of EE in digital technology environments, however, is inconclusive, with some studies indicating that ecosystem support can better facilitate learning in rapidly changing markets (Lopes et al., 2025) in decision-making. The present study tests whether EE has a significant impact on the strength of the DEE–DEB path, using an empirical approach.

Hypothesis Development

Derived from the theoretical background and constructs established previously, this section hypothesizes the relationship between the DEE and the DEB, which is achieved directly by the Entrepreneurial Ecosystem (DEE) and mediated through EINT and EINN. It adds a moderating role of EE on the strength of the relationships.

DEE and DEB

Digital ecosystems are becoming a key infrastructure for fostering entrepreneurship in the digital era. While DEE interventions may directly enable entrepreneurial behavior, as digital entrepreneurs rely on physical and institutional resources (such as funding, platforms, and digital policy), the establishment of a strong DEE is likely to be directly supportive of entrepreneurial behavior. Prior work (Kraus et al., 2022; Sussan & Acs, 2017) finds that a resource-rich, well-connected ecosystem stimulates digital startups to engage in opportunity discovery and exploitation. Hence, we propose:

H_1 : A strong DEE positively influences DEB.

Mediating Role of EINT

The TPB, proposed by Ajzen (1991), suggests that intention is the most proximal determinant of behavior. When the role of intention is also considered—as it is in entrepreneurial settings—it has an impact as a mediator between external factors (e.g., ecosystem support) and entrepreneurial behavior (Liñán & Fayolle, 2015). A facilitating DEE could amplify perceived potential to avoid and report, and thus intent. A stronger intention is related to a greater likelihood of enacting the behavior. Thus, we hypothesize:

H_2 : DEE has a positive and significant impact on EINT.

H_3 : EINT positively and significantly influences DEB.

H_4 : The relationship between DEE and DEB is mediated by EINT.

Mediating Role of EINN

Although EINT reflects one's motivation to engage in venture creation, intention itself is insufficient for DE. Execution involves the ability to innovate—to create new products, processes or business models in light of the rapid metamorphosis of digital technologies. This is a capability-based view downstream with Teece's (2007)

dynamic capability argument of the entrepreneur to sense, seize, and reconfigure resources in turbulent environments.

The Digital Entrepreneurial Ecosystem (DEE) can potentially be an important facilitator of innovation through providing access to advanced technologies, mentors, finance, and collaboration networks. Previous studies proposed that the more ecosystem support there is to meet the entrepreneurial capability, the more innovation will occur (Kraus et al., 2022; Zahra & George, 2002). Conversely, creative output, platform revamp, product digitization and data-based personalization can add much value to DEB. Hence, we propose:

- H_5 : DEE has a positive and significant effect on EINN.
- H_6 : EINN has a positive and significant effect on DEB.
- H_7 : EINN mediates the relationship between DEE and DEB.

EE: Direct and Moderating Role

EE plays a pivotal role in determining how individuals perceive and pursue entrepreneurial opportunities. EE helps in building an entrepreneurial mindset and skills, such as identifying opportunities, solving problems, and mitigating risk, that are essential in converting ideas into viable business ventures. Studies have consistently demonstrated that exposure to entrepreneurial learning environments enhances a positive attitude toward business creation.

In this context, the value of EE goes beyond traditional classroom-based learning. Digital entrepreneurs often acquire essential skills and insights through non-conventional learning in ecosystems and collaborative communities in the marketplace. These learnings prepare them with the dexterity and digital fluency required to navigate complex challenges. Consequently, EE is hypothesized to exert a direct and moderating effect on the ecosystem’s outcome. Thus:

- H_8 : EE has a direct positive effect on DEB.
- H_9 : EE moderates the relationship between DEE and DEB.

The proposed research framework depicting the hypothesized relationships is presented in Figure 1.

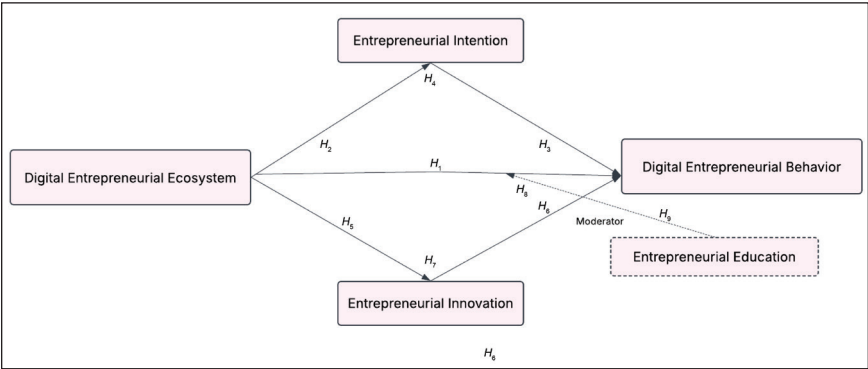


Figure 1. Proposed Framework.

Research Methodology

Measures

DEE was measured using a 3-item scale based on Sussan and Acs (2017) that assesses digital infrastructure availability, supportive policy and digital funding (DEE) was the third dimension measured. EINT was measured by some items adopted from Liñán and Chen (2009) to inquire about the readiness and intention of respondents to create a digital enterprise. EINN was assessed by a scale based on dynamic capability literature (Teece, 1997) that reflects innovation behavior by the capacity to sense, seize and reconfigure digital opportunities.

To measure the DEB, a 5-construct scale (Autio et al., 2018; Nambisan, 2017) was used, including the presence of digital platforms, digitization of products, data-driven decision-making, and the customers' online involvement. The moderator, EE, was operationalized with a 3-item scale adapted from the one developed by Nabi et al. (2017) as a proxy for exposure to entrepreneurship training.

All the constructs were measured using reflective multi-item scales from prior research. This enhances the reliability and establishes a good content validity for DEE, DEB, EINT, EINN and EE constructs. The measures have been reported on in the results (reliability and validity).

Sample and Data Collection Procedure

A web survey was created to collect data from digital entrepreneurs. Responses with 10% missing data were removed from the analysis to preserve the integrity of the data (Podsakoff et al., 2023). Data pre-screening was conducted in IBM SPSS 30 to investigate the missing values, the presence of outliers, and to examine the normality of the inherent data.

The demographic statistics for the respondents are relatively evenly distributed in terms of age, education, industry sector, and number of complete years in digital business. Participation was voluntary, and all respondents were guaranteed confidentiality and protection of their information.

Data was collected from the respondents using a purposive and snowball sampling approach. In view of the expanding nature of this industry and the lack of a single centralized database for digital entrepreneurship, purposive sampling allows us to choose only the appropriate respondents—individuals who are currently involved in the digital entrepreneurship marketplace. As a result, the contributions from individuals exploring the Realm of Digital Entrepreneurship are more robust and reflective. In addition, we use snowball sampling to extend the sample by leveraging personal networks of entrepreneurs, incubators and startup communities.

As digital entrepreneurs frequently work in networks, the method proves efficient in locating otherwise obscure respondents who are not immediately available for randomized selection. This approach has been employed in studies of entrepreneurial networks and digital ecosystems, demonstrating its validity.

Data gathering was carried out through a structured online questionnaire sent to entrepreneurial incubators, digital business communities, and professional sites (LinkedIn and startup forums). 343 responses were collected from digital entrepreneurs in a scalable manner, which delivers a diverse and representative sample (Wright, 2005).

The respondents, consisting of digital entrepreneurs, startup founders, and executives, are actively engaged in the DEE. Below is the breakdown of the sample characteristics:

Table 1 presents the sample characteristics of the study, respondents, primarily consisting of digital entrepreneurs, startup founders, and executives actively engaged in the DEE.

The majority of participants (62.7%) were founders or co-founders, while 37.3% were C-level executives. The industry distribution shows that 29.7% of startups operate in e-commerce, followed by Fintech (21.6%), Edtech (16.3%), HealthTech (13.7%), and SaaS & AI-driven startups (11.1%), with the remaining 7.6% categorized as others.

In terms of startup age, 42.0% were in the early stage (1–3 years), 35.6% were between 4 and 6 years, and 22.4% had been operating for over seven years. Regarding funding status, 28.0% of the startups were bootstrapped, 30.6% had received angel funding, and 41.4% were backed by venture capital.

These characteristics highlight the diverse representation across roles, industries, startup maturity, and funding stages, ensuring a comprehensive examination of digital entrepreneurship dynamics.

Common Method Bias

Both procedural and statistical remedies were employed to mitigate possible CMB. Items were placed non-adjacently in the questionnaire, and item wording

Table 1. Sample Characteristics.

Characteristic	Category	Count (n = 343)	%
Role	Founder/co-founder	215	62.70
	C-level executive	128	37.30
Industry sector	E-commerce	102	29.70
	Fintech	74	21.60
	Edtech	56	16.30
	HealthTech	47	13.70
	SaaS & AI-driven startups	38	11.10
	Others	26	7.60
Startup age	1–3 years	144	42.00
	4–6 years	122	35.60
	7+ years	77	22.40
Funding status	Bootstrapped	96	28.00
	Angel-funded	105	30.60
	Venture capital-backed	142	41.40

was counter-balanced. Statistically, Harman's single-factor test did not show a single dominant factor, as the first factor did not account for 40% of the variance. A standard latent factor test was also performed in SmartPLS, which verified that CMV had not posed a serious problem.

Data Analysis Strategy

The testing of the structural model was conducted using SmartPLS 4.0 with Partial Least Squares Structural Equation Modeling (PLS-SEM), which is an appropriate technique for research that uses models that are theoretically complex and have unobserved constructs, as well as when the number of observations is modest (Hair et al., 2017). The method allows for simultaneous testing of measurement validity and structural paths, including not only reflective indicators, but also moderation/mediation paths.

After model fitting, diagnostic tests were also conducted to test the validation, robustness and fit of the statistical assumption. Multicollinearity was examined using variance inflation factor (VIF) values of all the predictor constructs from 1.9 to 2.1, indicating an acceptable range (Hair et al., 2021). The reliability and convergent and discriminant validity were tested based on typical PLS-SEM criteria.

The analysis was conducted in SmartPLS 4 using PLS-SEM. Bootstrapping with 5,000 resamples was applied to test the significance of direct, indirect, and moderating effects (Chin, 1998).

Results

Measurement Model Assessment

To achieve measurement robustness, the model was tested for reliability and validity (Refer Table 3) according to PLS-SEM guidelines. The internal consistency of each scale was examined through Cronbach's Alpha (α) and Composite Reliability (CR). There were three constructs, DEE, EINT and EINN, that surpassed the level of the α at 0.70. Nevertheless, DEB and EE have slightly lower α values of 0.641 and 0.659, respectively. However, both constructs elicited high CR values (over 0.85), indicating satisfactory reliability. In exploratory research, as in the present, a Cronbach's alpha of more than 0.60 is acceptable when it is guided by the high CR and convergent validity (Hair et al., 2021; Nunnally & Bernstein, 1994).

Convergent validity was established by examining the Average Variance Extracted (AVE), which was greater than the threshold value of 0.50 for all constructs, suggesting that the constructs capture more variance than measurement error (Fornell & Larcker, 1981). These findings indicate that the constructs are internally consistent and have convergent validity for structural modeling.

Discriminant validity was assessed through the Fornell–Larcker criterion (Refer Table 4), cross-loadings and the Heterotrait–Monotrait (HTMT) ratio

(Refer Table 5). Fornell–Larcker tests indicated that the square roots of the AVE for each construct were greater than the constructs’ correlations with all other constructs, respectively, implying that each construct shared more variance with its measures than with other latent variables. In addition, the HTMT values from all pairs of constructs were lower than the very conservative threshold (HTMT < 0.85), suggesting that discriminant validity was satisfied (Henseler et al., 2015). Collectively, these data show that the constructs are empirically distinct and can be further tested structurally.

All scale items were reflective and are presented in Appendix.

Multicollinearity Assessment

The VIF (Refer Table 2) was used to evaluate multicollinearity, that is, whether predictor variables were independent. The VIF values were less than 5 for all the predictors as suggested by Hair et al. (2021). These results signify that individual

Table 2. VIF Assessment for Predictor Variable.

Predictor Variable	VIF
Entrepreneurial Intention (EINT)	1.339
Entrepreneurial Innovation (EINN)	1.135
Entrepreneurial Education (EE)	2.112

Source: Primary data.

Table 3. Construct Reliability and Validity Assessment.

Construct	Item	Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
DEE	DEE1	0.86	0.742	0.896	0.742
	DEE2	0.84			
	DEE3	0.89			
DEB	DEB1	0.79	0.641	0.899	0.641
	DEB2	0.8			
	DEB3	0.82			
EE	EE1	0.74	0.659	0.853	0.659
	EE2	0.77			
	EE3	0.79			
EINT	EINT1	0.86	0.764	0.907	0.764
	EINT2	0.87			
	EINT3	0.85			
EINN	EINN1	0.82	0.73	0.89	0.73
	EINN2	0.8			
	EINN3	0.85			

Source: Primary data.

Table 4. Discrimination Validity (Fornell–Larcker Criterion).

	DEE	DEB	EINT	EINN	DEE
DEE	0.861				
DEB	0.549	0.801			
EINT	0.251	0.372	0.812		
EINN	0.503	0.478	0.124	0.874	
DEE	0.345	0.506	0.3	0.309	0.854

Source: Primary data.

Table 5. Heterotrait–Monotrait Ratio (HTMT).

	DEE	DEB	EINT	EINN
DEE				
DEB	0.31			
EINT	0.602	0.561		
EINN	0.413	0.6	0.378	

Source: Primary data.

predictor variables separately explain the variance in the dependent variable, and in turn, they assure the PLS-SEM regression estimate reliability (Sarstedt et al., 2019).

Structural Model Assessment

The goodness of fit of the structural model has been confirmed and tested in order to analyze the proposed relationships. This process was conducted using a bootstrapping test to generate standard errors and confidence intervals for statistical validity (Hair et al., 2021). This process directly alleviates the reliance on distributional requirements and is therefore more appropriate for PLS-SEM analysis.

Testing of Hypothesis and Path Coefficients

The *t*-test and *p* value examined the associations with 95% CI. Additionally, a path was to be statistically significant if the confidence interval around it did not contain zero, signifying that there was a test effect (Chin, 1998).

While these results are somewhat counterintuitive, they generally support the resilience of the digital entrepreneurial ecosystem in influencing entrepreneurial behavior regardless of formal educational interventions, and highlight the need for policy and industry organizations to support ecosystem development rather than focusing solely on education-driven entrepreneurship programs.

The findings emphasize the crucial role of the DEE in shaping DEB, EINT, and EINN. Due to the direct impacts of DEE to DEB ($\beta = 0.501, p < .001$), EINT ($\beta = 0.503, p < .001$) and EINN ($\beta = 0.345, p < .001$), supporting the notion that a supportive entrepreneurial environment does indeed have a positive impact on entrepreneurial behavior, intrinsic motivation, and innovation.

Moreover, EINT ($\beta = 0.223, p < .001$) and EINN ($\beta = 0.281, p < .001$) have significant effects on DEB. The implication is that entrepreneurs with intentions and innovative abilities are both more likely to be involved in digital entrepreneurship.

Furthermore, EE has a direct positive effect on DEB ($\beta = 0.187, p < .001$), reinforcing the importance of structured learning in fostering digital entrepreneurship. However, the interaction between EE and DEE ($\beta = 0.046, p = .156$) was not statistically significant, indicating that EE does not significantly moderate the relationship between the digital entrepreneurial ecosystem and DEB. The hypothesis testing results are summarized in Table 6.

Mediation Analysis

The bootstrapping method with 5,000 resamples was used to assess the indirect effects of EINT and EINN as mediators between the DEE and DEB. Mediation (Refer Table 7) was evaluated using the approach outlined by Baron and Kenny (1986) and Muller et al. (2005), which confirms mediation when the following conditions are met:

1. DEE has a significant direct effect on DEB in the absence of the mediator.
2. DEE significantly influences the mediators (EINT and EINN).

Table 6. Hypothesis Testing.

Hypothesis	Path	β (Path Coefficient)	t-statistics	p Value	Support
H_1	DEE $\rightarrow$ DEB	0.293	6.076	<.001	Supported
H_2	DEE $\rightarrow$ EINT	0.503	12.289	<.001	Supported
H_3	EINT $\rightarrow$ DEB	0.223	4.581	<.001	Supported
H_4	EE $\rightarrow$ EINT $\rightarrow$ DEB	0.112	3.986	<.001	Supported
H_5	DEE $\rightarrow$ EINN	0.345	6.854	<.001	Supported
H_6	EINN $\rightarrow$ DEB	0.281	6.28	<.001	Supported
H_7	EE $\rightarrow$ EINN $\rightarrow$ DEB	0.097	3.548	<.001	Supported
H_8	EE $\rightarrow$ DEB	0.187	4.499	<.001	Supported
H_9	EE $\times$ DEE $\rightarrow$ DEB (moderation)	0.046	1.419	.156	Not Supported

Source: Primary data.

Table 7. Mediation Analysis Results.

Path	Indirect Effect (β)	t-statistic	p Value	Confidence Interval (95%)	Mediation Type
DEE $\rightarrow$ EINT $\rightarrow$ DEB	0.112	3.854	0	[0.064, 0.178]	Partial mediation
DEE $\rightarrow$ EINN $\rightarrow$ DEB	0.097	3.526	0	[0.048, 0.163]	Partial mediation

Source: Primary data.

Table 8. Variance Accounted For (VAF) Analysis—Mediation Strength and Effect Decomposition.

Path	Indirect Effect (β)	Direct Effect (β)	Total Effect	VAF (%)	Mediation Type
DEE → EINT → DEB	0.112	0.501	0.613	18.27	Weak mediation
DEE → EINN → DEB	0.097	0.501	0.598	16.22	Weak mediation

Source: Primary data.

- 3. The mediators significantly affect DEB while controlling for DEE.
- 4. The DEE on DEB weakens upon inclusion of the mediators, indicating partial mediation.

The Variance Accounted For (VAF) (Refer Table 8) approach tests how much the mediation effect can explain the total effect (Sarstedt et al., 2016). Weak mediation effect of EINT (VAF = 18.27%) and EINN (VAF = 16.22%) indicates that though these constructs converge the benefits of DEE into DEB, there are other factors also accomplishing this essential role.

Partial mediation of EINT implies that intention is not the only factor that determines entrepreneurial behavior, but that ecosystem factors continue to play a substantial role independently. Furthermore, while according to the model, the mediation effect of EINN demonstrates the relative value of innovation for digital entrepreneurship, ecosystem support—in terms of finance and infrastructure—remains a more important factor. The mediation effects of EINT and EINN are detailed in Table 7.

In general, these results provide support that DEE has a significant direct and indirect effect on entrepreneurial behavior; however, intention and innovation are not enough to predict digital entrepreneurship. Further interventions, such as access to market and mentoring, may be required to enhance the mediation effect and maximize entrepreneurial success in digital ecosystems. The structural model illustrating the tested relationships is shown in Figure 2.

Moderation Analysis

The Product Term Approach (Baron & Kenny, 1986; Hayes, 2013) was used to study the moderation effect of EE in the relationship between DEE and DEB among the entrepreneurs. This model incorporates an interaction term (DEE × EE) to test moderation while accounting for the direct association between DEE and DEB.

1. Moderation Results

The findings (Refer Table 9) show that EE does not significantly moderate the DEE–DEB relations ($\beta = 0.046$, $t = 1.419$, $p = .156$). The 95% CI [−0.017, 0.108] involves the value zero, which means the moderation effect is not statistically significant.

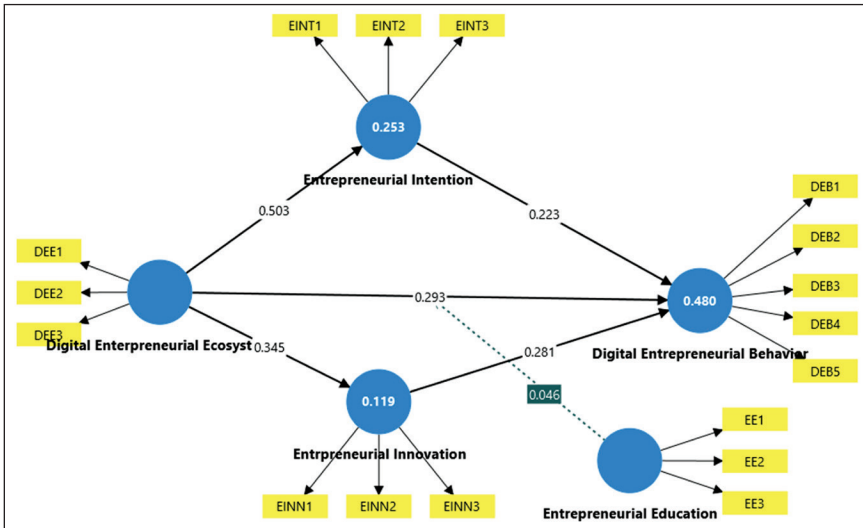


Figure 2. Structural Model for Digital Entrepreneurial Behavior.

Table 9. Moderation Analysis Results.

Path	β (Path Coefficient)	t-value	p Value	Confidence Interval (95%)	Moderation Significance
DEE $\times$ EE $\rightarrow$ DEB	0.046	1.419	.156	[-0.017, 0.108]	Not significant

Source: Primary data.

2. Interpretation of Moderation Analysis

EE, in a digital context, does not directly impact DEE on DEB. This may be because existing patterns for developing and implementing EE in new contexts are based on a more traditional model, with limited experience and digital elements. Lack of proximal ecosystem factors, such as financial access and infrastructure supports, may have a greater impact on the level of digital entrepreneurial engagement compared to educational interventions. A low moderation for EE signifies that the ecosystem is more influential than education in driving digital entrepreneurial ventures.

Model Fit and Predictive Power

The structural model's explanatory and predictive capabilities were evaluated using R^2 , Q^2 , and f^2 statistics. The R^2 values indicate moderate to substantial explanatory power for the key dependent constructs. The predictive relevance (Q^2) was assessed using PLSpredict in SmartPLS4; the Q^2 values were above zero, confirming acceptable predictive relevance (Refer Table 11). Additionally, the f^2 effect sizes suggest that the predictor variables exert meaningful influence on their respective outcomes, with magnitudes ranging from small to large in accordance

with Cohen's (1988) benchmarks. Overall, the model demonstrates both statistical robustness and practical relevance.

Predictive Relevance (Q^2) Results

All Q^2 values were greater than zero, indicating predictive relevance of the model for the respective endogenous constructs.

Table 10 presents the coefficient of determination (R^2) values, indicating the model's explanatory power. DEB demonstrates moderate explanatory strength, while EINT and EINN show weaker predictive power, suggesting that additional influencing factors may contribute to the formation of intention and innovation beyond the DEE.

Table 12 reports the effect size (f^2) for each pathway, revealing that most predictors have small to medium effect sizes. Despite the lower magnitudes, the statistical significance of these relationships highlights their practical relevance in explaining DEB. The interaction effect ($DEE \times EE \rightarrow DEB$) demonstrates a negligible influence, reinforcing the earlier finding that EE does not significantly moderate the relationship between DEE and DEB in this context.

Table 10. Explanatory Power of Endogenous Constructs.

Construct	R^2 Value	Explanatory Strength
Digital Entrepreneurial Behavior (DEB)	0.498	Moderate
Entrepreneurial Intention (EINT)	0.253	Weak
Entrepreneurial Innovation (EINN)	0.185	Weak

Source: Primary data.

Table 11. Predictive Relevance (Q^2) Assessment.

Construct	Q^2 Value	Predictive Strength
Digital Entrepreneurial Behavior (DEB)	0.367	Moderate to strong
Entrepreneurial Intention (EINT)	0.176	Weak to moderate
Entrepreneurial Innovation (EINN)	0.152	Weak to moderate

Source: Primary data.

Note: The results confirm that the model has predictive relevance, particularly for DEB.

Table 12. f^2 Effect Size Analysis.

Path	f^2 Value	Effect Size
DEE $\rightarrow$ DEB	0.087	Small
DEE $\rightarrow$ EINT	0.339	Medium
DEE $\rightarrow$ EINN	0.227	Small to medium
EINT $\rightarrow$ DEB	0.096	Small
EINN $\rightarrow$ DEB	0.123	Small to medium
EE $\times$ DEE $\rightarrow$ DEB	0.004	Negligible

Source: Primary data.

Discussion

The findings reaffirm that the DEE has direct and indirect influence on the DEB through EINT and EINN. The results highlight the centrality of ecosystem enablers—digital infrastructure, institutional support and mentorship—in seeding digital entrepreneurship. The significant direct impact of DEE on DEB provides strong evidence that digital entrepreneurs are primarily influenced by resources and support systems within their ecosystem.

Interestingly, the study also reveals that while EE directly affects DEB, its moderating effects in strengthening the DEE–DEB path were statistically non-significant. This could indicate, then, that an EE is not so much about being a contingent factor as acting as a common enabler. Education, therefore, enables entrepreneurs generally from a broader base but does not always increase the ecosystem effects on behavior, unless attuned to digital startup contexts. This result is consistent with the growing and predominant view in the literature, which suggests that effects of EE are more potent when curricula are experiential, technology-focused, and context-bound (Fayolle et al., 2022).

The mediation of EINT and EINN has a significant but modest effect. The above outcomes have theoretical implications and indicate that DEE not only has a direct influence on behavior, but it also significantly influences entrepreneurial attitudes and creativity as psychological and behavioral mechanisms. This is consistent with the TPB and Innovation Diffusion Theory (IDT) that entrepreneurial behavior is determined by the intention and perceived innovativeness in favorable conditions.

Theoretical Implication

This study offers important theoretical contributions by expanding three theoretical pillars—the influence of Institutional Theory, the TPB, and IDT—in the context of digital entrepreneurship.

First, through empirical evidence, the results corroborate and extend the Institutional Theory-based view by highlighting that formal and informal ecosystem structures (e.g., regulation, incubation, and digital platforms) have a significant impact on entrepreneurial behavior. Although institutional support has been studied in relation to traditional entrepreneurship, this study contextualizes these constructs in digitally mediated settings and thus extends Institutional Theory's boundary conditions to online resource systems and platform governance as institutional actors.

Second, in verifying the mediating role of EINT, this research extends the TPB to a digital entrepreneurial context. TPB has been broadly applied to account for entrepreneurial behavior in the literature; however, there is scant research related to the TPB in digital ecosystems. This study adds by demonstrating that the intention building process remains important in the context of digital, but is heavily impacted by ecosystem support—suggesting that exogenous systemic variables can work indirectly through the formation of intention to influence planned behavior.

Third, the mediating effect of EINN on digital entrepreneurial behavior provides support for and further explanation of the IDT. While IDT typically takes the user's perspective with respect to the spread of innovation, in this case, it is used to characterize the entrepreneur as an honest-to-good innovator. It suggests that innovation capability in digital operations is not so much an attribute of the product as a behavior made possible by the ecosystem. This conceptualization provides a double vision: innovation as a consequence and as a driver of entrepreneurial behavior.

Taken together, these views provide some stage building for a better understanding of digital entrepreneurship by integrating institutional scaffolding, individual intentionality, and dynamics around innovation. The theoretical framework of the study highlights the importance of cross-level integration (i.e., linkage of macro-level ecosystem enablers toward micro-level psychological processes) in influencing DEB.

Managerial and Policy Implications

The study provides practical implications for practitioners, educators and policymakers seeking to foster digital entrepreneurship. Among the key findings that emerge from our analysis is the primacy of DEE in influencing entrepreneurial behavior both directly and indirectly. For incubators, accelerators and ecosystem enablers, this shows the need for structured technology-oriented support mechanisms—like mentorship in platform strategies, funding access, and regulatory facilitation. Furthermore, digital startups thrive when they are embedded in ecosystems that not only provide access to resources but also reduce uncertainty in dynamic markets.

From a management perspective, the reflexive effect that EINN has on Intention indicates that support efforts should be more than infrastructure provision. Managers at entrepreneurial support organizations may find it beneficial to focus on programs that activate cognitive and innovative skills—e.g., design thinking workshops, rapid prototyping labs, and peer-learning cohorts—because these are the most direct and impactful drivers of founder behavioral-change outcomes. Creating a sense of purpose and readiness for innovation is just as important as money or technical infrastructure.

The direct impact of EE highlights the shift in entrepreneurial learning in digital environments. Elaborating, the traditional curriculum-based programs play a significant role, but this study supports the broader conception of EE—incorporating experiential learning and informal learning through activities such as incubators, accelerators, peer networks, digital bootcamps and platform-based upskilling. Such pedagogies are agile and context aware, allowing entrepreneurs to learn just in time, to adjust on the fly, and to experiment iteratively. Given that the effect of EE is direct rather than one that moderates the relationship between the ecosystem and behavior, it seems that educational inputs do prepare the entrepreneur separately but may not always enhance the effect of the exogenous ecosystem, unless they are closely connected. This insight emphasizes the need to

reconceptualize teaching and to create integrated learning environments that combine school-based education with authentic, embedded experiences.

Policymakers can also draw insights from this study. Institutions should finance digitally adaptive policy infrastructure, like startup sandboxes, digital compliance toolkits and incentives for platform-based innovation. Second, closer university–industry–government collaboration is an important driver that speeds up the systemic embedding of EINT and innovation in regional economic development strategies.

Overall, our findings encourage a more holistic, capability-based, context-sensitive perspective on supporting digital entrepreneurs—one that links higher-level macro-ecosystem support to the micro-foundational competencies.

Societal Implications

This research highlights how digital entrepreneurship shapes inclusive economic and social futures beyond managerial applications. Through the examination of behavioral mechanisms, such as entrepreneurship, innovation capability, and self-learning, this examination underscores the democratization potential of digital systems. The digital economy is becoming more inclusive of different socio-economic and geographic groups, beyond traditional tech hubs.

The transition is leading to more open participation in innovation-driven economies. Conducive ecosystem for startups, cloud-based digital services, and low-capital models allow underrepresented groups—such as women, people who live in rural areas, and first-time entrepreneurs—to contribute economically.

Digital entrepreneurship facilitates bottom-up change, economic empowerment and shifts in culture toward innovativeness and self-sufficiency. These changes are the heart of civilization’s advancement in digital economies and even more in developing economies like India.

Limitations and Future Research Design

Although this research presents valuable reflections on digital entrepreneurial action, limitations should be acknowledged to guide future research. First, the study design was cross-sectional; it was impossible to draw causal inferences from the data. Longevity studies have the potential to better comprehend changes in DEB over time in relation to ecosystem and policy shifts.

Second, despite the strong sample size of 343 respondents, all participants came from India. Therefore, the external validity of the reported results to other situational or institutional settings, particularly other countries with different degrees of digital maturity, regulatory development and entrepreneurial culture, may be limited. Cross-country comparative analyses are needed to test the model in different digital ecosystems.

Third, the use of self-report measures may be vulnerable to common method bias and social desirability effects, notwithstanding steps taken to mitigate this. The inclusion of secondary data (e.g., venture performance, funding rounds, or

digital engagement metrics) could yield a richer, triangulated analysis of entrepreneurial activity and outcomes.

Fourth, although in this study, EE was analyzed, a distinction between formal education and informally acquired knowledge from guidance by coaches or from acceleration programs was not made. It would be interesting for future research to investigate how different forms of educational intervention (e.g., type and intensity) differentially engage behavior—especially in online settings, which are characterized by decentralized and experiential-in-the-wild learning.

Finally, a limited number of variables were examined in the study—DEE, EE, EINT, and EINN. It is possible that extending the model to include other individual-level factors, for example, entrepreneurial self-efficacy, digital resilience, or platform capability, would help us to delineate more clearly what drives success in digital entrepreneurship.

By dealing with these challenges, future inquiry may refine theoretical considerations and enhance the practical applicability of entrepreneurial ecosystem studies in digital economies.

Conclusion

Comprehensive analyses of the determinants of DEB of an integrative framework elucidating ecosystem support (DEE), EINT, EINN, and EE. Applying PLS-SEM on a sample of 343 digital entrepreneurs, the study validates direct and indirect effects on entrepreneurial behavior. The findings contribute to theory development by applying Institutional Theory, TPB, and IDT to the context of digital entrepreneurship. A key finding from the study is that despite the high level of direct impact of ecosystem support, impact is also furthered through internal processes such as intention and innovation. The non-significant moderating position of EE is indicative of a foundational, rather than an amplificatory, part of education's role, particularly in the context of informal, situated learning. All those findings hold important implications for researchers, educators, ecosystem managers, and policymakers. More broadly, the findings of this study add to the emerging body of research on digital entrepreneurship and provide a platform upon which future research can develop, extending from both its conceptual and empirical underpinnings.

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Appendix

Construct	Code	Measurement Item
Digital Entrepreneurial Behavior (DEB)	DEB1	Our business has successfully expanded into digital markets.
	DEB2	We actively adopt digital technologies to enhance operations.
	DEB3	Online platforms play a crucial role in our business growth.
	DEB4	We leverage data analytics for business decision-making.
	DEB5	Digital channels significantly contribute to our revenue.
Digital Entrepreneurial Ecosystem (DEE)	DEE1	The ecosystem provides access to essential digital resources.
	DEE2	Government and private initiatives support digital startups.
	DEE3	Infrastructure and networks foster digital business growth.

(Appendix continued)

(Appendix continued)

Construct	Code	Measurement Item
Entrepreneurial Education (EE)	EE1	Formal training improves my digital entrepreneurship skills.
	EE2	Entrepreneurship programs enhance digital business knowledge.
	EE3	Workshops and mentorship have helped in digital transformation.
Entrepreneurial Innovation (EINN)	EINN1	We frequently introduce innovative digital business models.
	EINN2	Our company invests in digital R&D for innovation.
	EINN3	Technological advancements drive our innovation strategy.
Entrepreneurial Intention (EINT)	EINT1	I am determined to establish a digital business.
	EINT2	I see digital entrepreneurship as a career path.
	EINT3	I actively seek opportunities in digital markets.