# When Learning Doesn't Lead to Innovation: Digital Rent as an Alternative Pathway for SME Business Model Innovation

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## Abstract

This study examines whether absorptive capacity mediates the relationship between digital capability and business model innovation (BMI) in manufacturing SMEs operating in a least developed, post-conflict context. Using hierarchical regression on survey data from 300 manufacturing SMEs in Liberia, we test direct effects of digital capability on four BMI dimensions (value creation, proposition, delivery, and capture) and the mediating role of absorptive capacity. The findings reveal three novel insights. First, digital capability strongly and directly drives all four BMI dimensions, confirming it as a valuable strategic resource even under extreme resource constraints. Second, while digital capability significantly enhances absorptive capacity absorptive capacity does not mediate the digital capability BMI relationship. Third, we introduce the concept of digital rent value appropriation through cost-side efficiency gains rather than revenue-side innovation to explain why theoretically expected mediation fails in resource-constrained environments. This study makes two primary contributions: it extends absorptive capacity theory by identifying a critical boundary condition in post-conflict, institutionally weak contexts, and it challenges the universal applicability of Western-centric mediation models. Practically, the findings suggest that SME managers and policymakers should prioritize direct digital tool deployment over complex knowledge absorption programs in severely resource-constrained settings.

**Keywords**: Digital capability, absorptive capacity, business model innovation, SMEs, Liberia, digital rent

## 1. Introduction

In developing economies, small and medium-sized enterprises (SMEs) face persistent structural constraints unreliable infrastructure, limited access to finance, and institutional fragility that severely restrict their capacity for traditional product or process innovation (Diallo et al., 2023; World Bank, 2025). In such environments, business model innovation (BMI) the strategic reconfiguration of value creation, delivery, and capture mechanisms emerges as a critical pathway for survival and growth (Foss & Saebi, 2017; Teece, 2018). Digital technologies are widely promoted as enablers of such transformation, yet a growing body of literature documents a "digital paradox": substantial investments in digital tools often fail to yield commensurate innovation outcomes, particularly in resource-constrained SMEs (Ancillai et al., 2022; Vaska et al., 2021). This indicates that the relationship between digital capability and BMI is not automatic but likely depends on complementary organizational capabilities, particularly absorptive capacity the firm's ability to acquire, assimilate, transform, and exploit external knowledge (Cohen & Levinthal, 1990). However, empirical evidence on whether absorptive capacity serves as the mediating mechanism linking digital capability to BMI remains inconclusive, especially in least developed country contexts.

Liberia provides a theoretically fertile context for examining these dynamics. As a post-conflict economy where manufacturing SMEs constitute approximately 80–90% of businesses and operate under conditions of extreme resource scarcity limited digital infrastructure, weak institutional support, unreliable electricity, and fragmented markets the country offers a natural laboratory for understanding how firms leverage internal capabilities to navigate institutional voids (World Bank, 2024). Despite the strategic importance of this context, empirical research examining the mediating role of absorptive capacity in driving digital-enabled BMI among manufacturing SMEs remains scarce. Existing studies predominantly employ linear methods such as hierarchical regression but often fail to explain why theoretically expected mediation effects do not hold in resource-constrained environments (Abubakar et al., 2019; Jonathan & Kuika Watat, 2020). This

gap is significant because understanding whether absorptive capacity transmits or merely accompanies digital capability's effects has critical implications for theory and practice.

This study addresses these gaps by investigating two research questions: (1) Does digital capability directly and positively influence all four dimensions of BMI value creation, value proposition, value delivery, and value capture among manufacturing SMEs in Liberia? (2) Does absorptive capacity mediate the relationship between digital capability and BMI in this resource-constrained context? To answer these questions, the study employs hierarchical regression on survey data from 300 Liberian manufacturing SMEs, enabling systematic testing of direct and mediating effects following Baron and Kenny's (1986) stepwise approach. The findings reveal three key results. First, digital capability strongly and significantly predicts all four BMI dimensions (β ranging from 0.446 to 0.531, $p < 0.001$), with value creation innovation showing the strongest effect, indicating that Liberian manufacturing SMEs leverage digital tools primarily for production efficiency and process integration. Second, while digital capability significantly enhances absorptive capacity, absorptive capacity does not translate into BMI, and the indirect effect is non-significant. Thus, H2 is rejected. Third, the study introduces the concept of digital rent to explain this finding: in resource-constrained environments, firms' appropriate value primarily through cost-side efficiency gains (e.g., process automation, supply chain coordination) rather than revenue-side innovation requiring complex knowledge transformation. These results challenge the universal applicability of absorptive capacity theory, demonstrating that in post-conflict, institutionally weak environments, SMEs bypass formal mediation pathways and rely on direct, efficiency-oriented digital deployment.

This study makes several contributions. Theoretically, it extends the resource-based view and dynamic capabilities theory by empirically demonstrating that digital capability directly drives all four dimensions of BMI in resource-constrained SMEs, confirming digital capability as a VRIN resource even in least developed country contexts. More importantly, it challenges absorptive capacity theory (Cohen & Levinthal, 1990; Zahra & George, 2002) by identifying a critical boundary condition: in post-conflict, institutionally weak environments, the theorized mediation pathway breaks down because firms prioritize direct, efficiency-oriented digital deployment over formalized knowledge absorption. The introduction of digital rent offers a new theoretical lens for

understanding digital transformation in severely resource-constrained settings where firms cannot afford exploratory learning and instead focus on immediate operational improvements. Methodologically, the study demonstrates the value of hierarchical regression for testing mediation pathways and identifying where theoretically expected mechanisms fail, providing a replicable framework for boundary condition research. Practically, the findings guide SME managers to invest directly in digital tools and infrastructure for immediate efficiency gains, rather than waiting for formal learning systems to be established. For policymakers in Liberia and similar contexts, the results suggest that supporting SME digital adoption through infrastructure investment, affordable digital tools, and basic digital literacy programs may be more immediately impactful than investing in advanced knowledge management or absorptive capacity development programs.

The remainder of this paper is organized as follows. Section 2 presents the literature review and theoretical foundation, including hypothesis development. Section 3 describes the methodology; Section 4 presents the results and discussion. Section 5 concludes, implications, limitations, and directions for future research.

## 2. Literature Review and Hypothesis Development

### 2.1 Theoretical Foundation

This study draws on four complementary theories to explain how digital capability drives business model innovation (BMI) in manufacturing SMEs in Liberia. The resource-based view (Barney, 1991) supports H1a–H1d by conceptualizing digital capability as a valuable, rare, inimitable strategic resource that enables SME innovation despite resource constraints. Dynamic capabilities theory (Teece et al., 1997) complements this by explaining digital capability as a higher-order mechanism for sensing, seizing, and reconfiguring resources to transform business models, further grounding H1a–H1d. Business model theory (Teece, 2018) provides the outcome framework for H1a–H1d by disaggregating BMI into four dimensions value creation, proposition, delivery, and capture allowing precise empirical testing. Absorptive capacity theory (Cohen & Levinthal, 1990) grounds H2 by specifying that digital capability expands external knowledge access, but absorptive capacity mediates the conversion of that knowledge into BMI outcomes. Finally, institutional theory (DiMaggio & Powell, 1983) does not generate a direct hypothesis but provides the contextual lens for interpreting anticipated null findings for H2, explaining why Western-centric

assumptions about learning may not hold in Liberia's post-conflict, resource-constrained institutional environment, thereby extending theory by specifying boundary conditions. Figure 2.1 presents the conceptual framework, which visually integrates these four theories into a single testable model linking digital capability to business model innovation. Figure 2.1 presents the conceptual framework, which visually integrates these four theories into a single testable model linking digital capability to business model innovation.

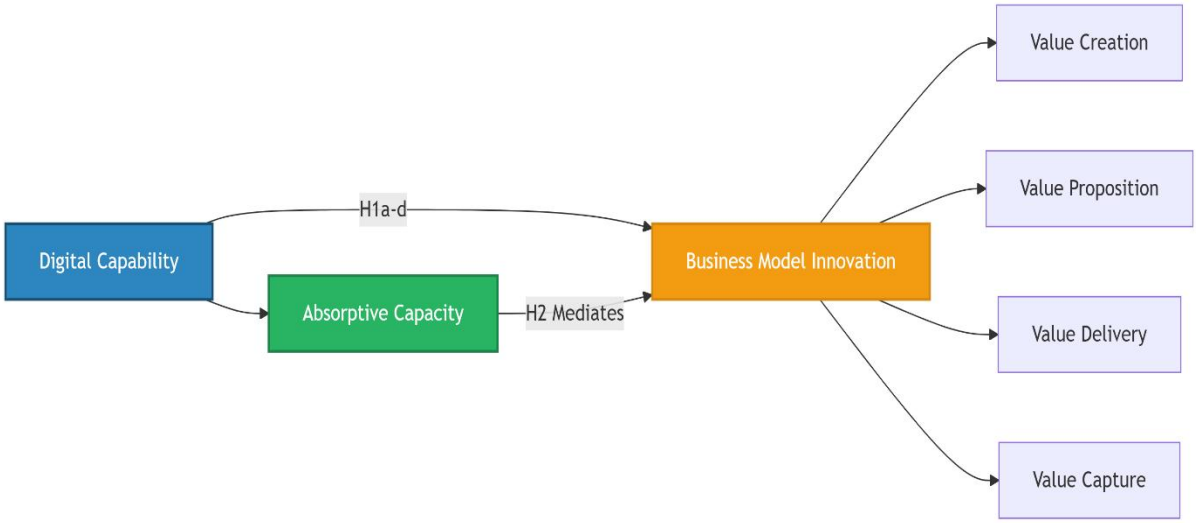


**Figure 2.1 Theoretical Framework**

## 2.2 Empirical Literature and Hypotheses Development

Drawing on the Resource-Based View (Barney, 1991), Dynamic Capabilities Theory (Teece et al., 1997), and Absorptive Capacity Theory (Cohen & Levinthal, 1990), this study develops hypotheses on how digital capability drives business model innovation (BMI) in manufacturing SMEs, and how absorptive capacity mediates this relationship.

### 2.2.1 Digital Capability and Business Model Innovation

Digital capability refers to a firm's ability to acquire, integrate, and leverage digital technologies to support strategic and operational objectives (Alrub & Sánchez-Cañizares, 2025; Ellström et al., 2022). Within the resource-based view, digital capability constitutes a valuable, rare, and inimitable strategic resource that enables SMEs to innovate despite resource constraints (Barney,

1991; Mailani et al., 2024). Dynamic capabilities theory complements this by explaining that digital capability functions as a higher-order mechanism for sensing digital opportunities, seizing them through strategic investments, and reconfiguring organizational resources to adapt to market change (Teece et al., 1997; Teece, 2025). Business model innovation involves purposeful changes in how firms create, deliver, and capture value (Teece, 2018; Huang & Ichikohji, 2023). This study disaggregates BMI into four dimensions: value creation innovation (changes in resource and process configuration), value proposition innovation (shifts in customer benefits), value delivery innovation (redesign of channels and engagement), and value capture innovation (new revenue and pricing models). Prior empirical evidence shows that digital capability enhances each of these dimensions. For example, digital tools improve production efficiency and process integration (value creation), enable data-driven product and service design (value proposition), facilitate digital channels and platform-based distribution (value delivery), and support experimentation with alternative revenue models (value capture) (Teoh et al., 2022; Fang et al., 2024). Therefore, this study proposes:

**H1a***: Digital capability is positively associated with value creation innovation.*

**H1b***: Digital capability is positively associated with value proposition innovation.*

**H1c***: Digital capability is positively associated with value delivery innovation.*

**H1d:** *Digital capability is positively associated with value capture innovation.*

### 2.2.2 The Mediating Role of Absorptive Capacity

Absorptive capacity theory explains how firms acquire, assimilate, transform, and exploit external knowledge for innovation (Cohen & Levinthal, 1990; Zahra & George, 2002). Digital capability expands SMEs' access to external knowledge from suppliers, customers, digital platforms, and industry networks (Carrasco-Carvajal et al., 2023; Kumar, 2025). However, the mere availability of information does not automatically translate into business model innovation. Absorptive capacity serves as the mediating mechanism that determines whether external digital knowledge is internalized, recombined with existing resources, and applied to redesign value creation, delivery, and capture mechanisms (Kastelli et al., 2024; Van Hoang et al., 2025). Empirical evidence demonstrates that digital capability has a stronger indirect effect on innovation performance through absorptive capacity than a direct effect alone (Kastelli et al., 2022). SMEs with stronger absorptive capacity are better able to translate digital knowledge into innovative value propositions, new delivery architectures, and adaptive revenue models (Miroshnychenko et

al., 2021; Sherani et al., 2025). Without sufficient absorptive capacity, digital investments remain confined to operational support rather than strategic business model transformation (Abubakar et al., 2019; Jonathan & Kuika Watat, 2020). Therefore, this study proposes:

**H2**: *Absorptive capacity mediates the relationship between digital capability and digital business model innovation.*

## 3. Methodology

### 3.1 Research design

This study employs a quantitative research design, which is consistent with its positivist paradigm and deductive approach. A quantitative design is justified because the study seeks to examine structured relationships among measurable organizational constructs and test specific hypotheses (H1a-H1d, H2) (Creswell, 2003). Quantitative methods enable systematic data collection, statistical testing of direct, moderating, and mediating effects, and generalization of findings across the population of manufacturing SMEs in Liberia. This design minimizes researcher bias, enhances reliability, and supports precise estimation of effect sizes essential for testing the proposed conceptual model.

### 3.2 Study Area

The study is conducted in Liberia, a post-conflict, least developed country in West Africa. Liberia is characterized by limited digital infrastructure, weak institutional support, resource-constrained SMEs, and uneven technological adoption making it an ideal context to test boundary conditions of Western-centric theories. Manufacturing SMEs in Liberia dominate the private sector (approximately 80-90% of businesses) and face persistent challenges including limited finance, unreliable electricity, and fragmented markets. These conditions provide a suitable empirical setting for examining how digital capabilities drive BMI under severe resource constraints, and mediation (H2) effects may not hold. Figure 3.1 shows the geographical location of Liberia.


**Figure 3.1 Liberia Map**

### 3.3 Population, Sampling and Sample Size

The target population comprises all manufacturing SMEs operating in Liberia, defined as firms with 10-250 employees engaged in manufacturing activities such as agro-processing, food production, wood and furniture, textiles, metal works, and construction materials. A purposive (judgmental) sampling technique was employed, as this non-probability approach allows deliberate selection of information-rich cases that meet specific criteria essential for addressing the research objectives (Ahmed, 2024). Firms were included if they: (1) employed 10–250 employees, (2) operated in the manufacturing sector, and (3) had implemented at least one digital tool within the past two years. Additionally, respondents were required to be senior decision-makers (owner-managers, CEOs, executives) possessing direct knowledge of digital practices and innovation activities. Firms outside the manufacturing sector, those with no recent digital tool adoption, and respondents lacking direct strategic decision-making roles were excluded, ensuring that only information-rich, qualified participants contribute to the study and enhancing data

validity and reliability. A structured questionnaire was administered to 350 manufacturing SMEs and after removing incomplete responses, the final sample comprised 300 firms.

### 3.4 Research Instrument and Measurement

A structured online questionnaire was used as the primary research instrument, justified by its efficiency, scalability, and suitability for collecting standardized data from geographically dispersed manufacturing SMEs (Elangovan & Sundaravel, 2021). The instrument employed closed-ended, five-point Likert-scale items (ranging from 1 = Strongly Disagree to 5 = Strongly Agree) to ensure consistency and compatibility with PLS-SEM analysis. Measurement scales were adapted from established and validated instruments: digital capability was measured using a seven-item scale from Prakasa and Jumani (2024) and Fang et al. (2024); business model innovation (encompassing value creation, value proposition, value delivery, and value capture) was adapted from Latifi et al. (2021) and Merín-Rodrigáñez et al. (2024); leadership capability was measured using scales from Fang et al. (2024) and Merín-Rodrigáñez et al. (2024); and absorptive capacity, operationalized as a higher-order construct comprising digital knowledge acquisition, assimilation, transformation, and exploitation, was adapted from Merín-Rodrigáñez et al. (2024) and Van Hoang et al. (2025). Control variables were included at both the individual level (gender, age, position, experience, education) and firm level (industry type, firm size) to reduce omitted variable bias and isolate the unique contributions of the main constructs (Fang et al., 2024).

### 3.5 Model Specification

To test the hypothesized relationships, this study specifies a hierarchical regression model with digital capability as the independent variable; the four dimensions of business model innovation (value creation, value proposition, value delivery, and value capture) as dependent variables; and absorptive capacity as the mediator (H2). This approach allows for the sequential addition of control variables, predictors, mediators, and interaction terms to examine incremental explanatory power ($\Delta R^2$) and to test mediation and moderation hypotheses.

#### Model 1-Control Variables Only

The first model included only control variables to account for potential confounding influences. These variables consisted of firm size, firm age, industry, employee working experience, gender,

work position, and educational level. Entering controls in the first step ensures that subsequent changes in explained variance can be attributed to the predictors of interest rather than extraneous factors, see equation 1.

$$BMI_i = \beta_0 + \beta_1 Controls_i + \varepsilon_i \quad (1)$$

**Model 2- Add Absorptive Capacity (Mediation H3):**

To test whether absorptive capacity (AC) mediates the relationship between digital capability (DC) and business model innovation (BMI), this study follows the stepwise approach of Baron and Kenny (1986). Mediation is established if four conditions are met: (1) DC significantly predicts BMI (path c, total effect); (2) DC significantly predicts AC (path a); (3) AC significantly predicts BMI when controlling for DC (path b); and (4) the direct effect of DC on BMI (path c') decreases significantly upon inclusion of AC, with the indirect effect (a × b) being statistically significant.

Three equations are estimated to test mediation. First, Equation (2) establishes the total effect of DC on BMI, controlling for relevant firm and demographic characteristics (path c). Second, Equation (3) tests whether DC significantly predicts AC (path a). Third, Equation (4) examines whether AC significantly predicts BMI when DC is included in the model (path b), while also providing the direct effect of DC (path c'). Mediation is supported if $\beta_2$ in Equation (3) is significant, $\beta_3$ in Equation (4) is significant, and the coefficient of DC ($\beta_2$) in Equation (4) is smaller in magnitude than in Equation (2). Additionally, the significance of the indirect effect (a × b) is confirmed using bootstrapped confidence intervals.

Equation (1): Total effect of DC on BMI (path c)

$$BMI_i = \beta_0 + \beta_1 Controls_i + \beta_2 DC_i + \varepsilon_i \quad (2)$$

Equation (2): Effect of DC on AC (path a)

$$AC_i = \alpha_0 + \alpha_1 Controls_i + \alpha_2 DC_i + \varepsilon_i \quad (3)$$

Equation (3): Direct effect of DC and effect of AC on BMI (path b and path c)

$$BMI_i = \beta_0 + \beta_1 Controls_i + \beta_2 DC_i + \beta_3 AC_i + \varepsilon_i \quad (4)$$

The change in explained variance ($\Delta R^2$) from Equation (1) to Equation (4) reflects the incremental contribution of AC beyond DC alone. A significant indirect effect ($\alpha_2 \times \beta_3$) with a bootstrapped 95% confidence interval excluding zero confirms mediation. If path b ($\beta_3$) is non-significant, mediation is not supported, indicating that AC does not function as the mechanism through which DC influences BMI in this context.

### 3.6 Data Analysis

Data analysis was conducted using hierarchical regression in SPSS in four stages. Stage 1 examined descriptive statistics and correlations. Stage 2 performed common method bias tests (Harman's single-factor and marker variable). Stage 3 executed hierarchical regression with sequential entry: Model 1 (controls), Model 2 (digital capability for H1a–H1d), Model 3 (absorptive capacity for H3 mediation). Standardized beta coefficients, p-values, and $\Delta R^2$ were reported at each step. Stage 4 performed diagnostic tests (VIF for multicollinearity, Breusch-Pagan and White for heteroskedasticity, Cook's distance for outliers), confirming that regression assumptions were satisfied and estimates were robust (Cohen, 2013; Aiken, 1991).

## 4. Result and Discussion

### 4.1 Demographic Characteristics

Table 1 presents the demographic profile of the 300 manufacturing SMEs and respondents. Regarding gender, male respondents comprised 59% (n = 177) and females 41% (n = 123), indicating a moderate male dominance in managerial positions within Liberia's manufacturing sector. In terms of firm age, the majority of SMEs fell within the 36–40 years (25%) and 41–45 years (24.3%) categories, while only 7.7% were above 50 years, suggesting a relatively mature but not aged SME population. Regarding respondent position, general managers represented the largest group (44.7%), followed by deputy managers (21.3%), branch managers (21%), and heads of department (13%), confirming that respondents held senior decision-making roles capable of providing reliable information on digital capabilities and innovation practices. For industry distribution, agro-processing and food manufacturing was the largest subsector (24.7%), followed by textile and garment (17.7%), metal works and construction materials (17.3%), and chemical and pharmaceutical products (15.6%). Regarding work experience, 32.3% of respondents had 5–10 years of experience, 30% had below 5 years, 22% had 11–15 years, and only 15.7% had above

15 years, indicating a relatively experienced but not highly seasoned managerial workforce. In terms of education, the majority held a bachelor's degree (49%), followed by master's degree (30%), high school (11.7%), and doctorate (9.3%), suggesting adequate educational qualifications for strategic decision-making. Finally, regarding SME size, medium-sized enterprises (50–250 employees) comprised the largest share (43.3%), followed by small enterprises (30.7%) and large enterprises (26%), reflecting a balanced representation across firm sizes.

**Table 1. Demographic Characteristics**

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 177 | 59% |
| | Female | 123 | 41% |
| Firm Age | Below 35 | 75 | 27.7% |
| | 36 – 40 | 83 | 25% |
| | 41 – 45 | 73 | 24.3% |
| | 46 – 50 | 46 | 15.3% |
| | Above 50 | 23 | 7.7% |
| Position | General Manager | 134 | 44.7% |
| | Deputy Manager | 64 | 21.3% |
| | Branch Manager | 63 | 21% |
| | Head of Department | 39 | 13% |
| Industry | Agro-processing and food manufacturing | 74 | 24.7% |
| | Wood, furniture, and timber products | 41 | 13.7% |
| | Textile, garment, and leather product | 53 | 17.7% |
| | Chemical, cosmetics, pharmaceutical, and | 47 | 15.6% |

| | | | |
|---|---|---|---|
| | household products manufacturing | | |
| | Metal works, construction materials, printing, and packaging manufacturing | 52 | 17.3% |
| | Other manufacturing | 33 | 11% |
| Work Experience | Below 5 years | 90 | 30% |
| | 5-10 years | 97 | 32.3% |
| | 11-15 years | 66 | 22% |
| | Above 15 | 47 | 15.7% |
| Education Level | High school | 35 | 11.7% |
| | Bachelor’s Degree | 147 | 49% |
| | Master’s Degree | 90 | 30% |
| | Doctorate | 28 | 9.3% |
| SMEs Size | Small (<50) | 92 | 30.7% |
| | Medium (50 -250) | 130 | 43.3% |
| | Large (>250) | 78 | 26% |

**Note.** Other manufacturing includes small-scale plastic and rubber products, artisanal soaps/candles, recycled materials, light building components, creative crafts, small electronics assembly, beverages, and other niche manufacturing activities

### 4.2 Descriptive Statistics

Table 2 presents the descriptive statistics for all study constructs measured on a five-point Likert scale. With a sample size of 300 SMEs, the mean scores ranged from 3.14 to 3.58, all above the midpoint of 3.0, indicating generally positive perceptions among respondents regarding digital capabilities and business model innovation. Digital Capability (DC) recorded the highest mean (M

= 3.58, SD = 0.58), followed by Leadership Capability (LC) (M = 3.47, SD = 0.88), Value Capture Innovation (VCA) (M = 3.39, SD = 0.89), Value Proposition Innovation (VPI) (M = 3.34, SD = 0.89), Absorptive Capacity (AC) (M = 3.28, SD = 0.81), Value Delivery Innovation (VDI) (M = 3.18, SD = 0.89), and Value Creation Innovation (VCI) (M = 3.14, SD = 0.92). The relatively higher mean for Digital Capability suggests that participating SMEs report stronger digital competencies compared to innovation outcomes, which aligns with the study's hierarchical regression findings that digital capability serves as the primary driver of BMI. Standard deviations ranged from 0.81 (AC) to 0.92 (VCI), indicating reasonable variability without excessive dispersion, which is essential for detecting significant relationships in hierarchical regression. Skewness values for all constructs were very close to zero (between -0.045 and 0.044), indicating approximately symmetric distributions, while kurtosis values were negative (approximately -1.15 to -0.98), reflecting slightly platykurtic distributions. These distributional properties confirm that the dataset is balanced and exhibits sufficient variability, providing an adequate empirical foundation for testing the direct (H1a–H1d), moderating (H2), and mediating (H3) relationships proposed in the study.

**Table 2 Descriptive Statistics**

| Construct | Items | N | Mean | Std Dev | Min | Max | Skewness | Kurtosis | Cramer-Von Test Statistic | Cramer - Von P-Value |
|---|---|---|---|---|---|---|---|---|---|---|
| AC | 5 | 300 | 3.280 | 0.810 | 1 | 5 | 0.036 | -1.145 | 0.453 | 0.000 |
| VCI | 8 | 300 | 3.140 | 0.920 | 1 | 5 | 0.044 | -1.091 | 0.327 | 0.000 |
| VCA | 7 | 300 | 3.390 | 0.890 | 1 | 5 | 0.019 | -1.121 | 0.381 | 0.000 |
| VDI | 6 | 300 | 3.180 | 0.890 | 1 | 5 | -0.009 | -1.148 | 0.458 | 0.000 |
| VPI | 6 | 300 | 3.340 | 0.890 | 1 | 5 | -0.032 | -1.063 | 0.302 | 0.000 |
| DC | 5 | 300 | 3.580 | 3.580 | 1 | 5 | -0.045 | -1.129 | 0.383 | 0.000 |
| LC | 4 | 300 | 3.470 | 3.880 | 1 | 5 | -0.039 | -0.985 | 0.259 | 0.001 |

Note. All latent variable scores are standardized (mean ≈ 0; standard deviation = 1) as generated by the PLS-SEM algorithm. Skewness and kurtosis values indicate generally symmetric but slightly

platykurtic distributions. The Cramér–von Mises test assesses normality; significant p-values suggest deviations from normality, which do not affect PLS-SEM estimation due to its non-parametric nature.

### 4.2 Baseline Result

The hierarchical regression results strongly support H1a–H1d, demonstrating that digital capability is positively and significantly associated with all four dimensions of business model innovation. As shown in Table 3, Model 2 significantly improves explanatory power across all dependent variables, with $\Delta R^2$ ranging from 0.180 to 0.256 ($p < 0.001$). Digital capability exhibits strong standardized coefficients: value creation innovation ($\beta = 0.531$, $p < 0.001$), value proposition innovation ($\beta = 0.483$, $p < 0.001$), value delivery innovation ($\beta = 0.446$, $p < 0.001$), and value capture innovation ($\beta = 0.477$, $p < 0.001$). These findings align with the Resource-Based View (Barney, 1991), which posits digital capability as a valuable, rare, and inimitable strategic resource that enables SME innovation despite resource constraints. They also support Dynamic Capabilities Theory (Teece et al., 1997), confirming that digital capability functions as a higher-order mechanism for sensing opportunities, seizing them strategically, and reconfiguring business models. The results are consistent with prior empirical evidence from Teoh et al. (2022) and Fang et al. (2024), who found that digital capability enhances value creation, proposition, delivery, and capture in SMEs. The particularly strong effect on value creation innovation ($\beta = 0.531$) suggests that Liberian manufacturing SMEs leverage digital tools primarily to improve production efficiency and process integration—a logical pathway given their resource-constrained environment where cost reduction is a priority. Thus, H1a–H1d are fully supported, confirming digital capability as the central strategic driver of multidimensional BMI in this context.

**Table 3. Baseline Result (H1a-H1d)**

| **Variables/Predictor** | **VCI (β)** | **VPI (β)** | **VDI (β)** | **VCA (β)** |
|---|---|---|---|---|
| Controls Only (Model1) | $R^2 = 0.020$ | $R^2 = 0.017$ | $R^2 = 0.025$ | $R^2 = 0.018$ |
| Age | 0.014 | 0.013 | -0.014 | 0.025 |
| Working Experience | 0.000 | 0.000 | 0.000 | 0.000 |
| Size | 0.116*** | 0.079* | 0.120*** | 0.086* |

| | | | | |
|---|---|---|---|---|
| Gender | 0.034 | 0.019 | 0.125* | 0.010 |
| Position | -0.000 | -0.029 | 0.006 | 0.008 |
| Education | 0.124*** | 0.105* | 0.136*** | 0.140*** |
| Controls+ DC (Model 2) | $R^2 = 0.276$ | $R^2 = 0.228$ | $R^2 = 0.206$ | $R^2 = 0.224$ |
| Digital capability (DC) | 0.531*** | 0.483*** | 0.446*** | 0.477*** |
| $\Delta R^2$ (DC) | 0.256 | 0.212 | 0.180 | 0.206 |
| F-change | 525.93*** | 407.63*** | 337.80*** | 395.80*** |

**Note.** Standardized coefficients (β) are reported. *p < .05, **p < .01, ***p < .001. Model 1 includes control variables only (firm age, working experience, firm size, gender, position, education level, and industry dummies). Model 2 adds Digital Capability (DC). $\Delta R^2$ represents the change in explained variance after the inclusion of DC. F-change statistics test the significance of the incremental variance.

### 4.3 Mediation Analysis

The mediation analysis in Table 4 demonstrates that absorptive capacity does not mediate the relationship between digital capability and BMI. Following Baron and Kenny's (1986) framework, Model 1 confirms a strong total effect of DC on BMI ($\beta = 0.737$, $p < 0.001$). Model 2 establishes path a: DC significantly predicts absorptive capacity ($\beta = 0.322$, $p < 0.001$), indicating that digital capability enhances knowledge acquisition and assimilation. However, Model 3 fails to establish path b: absorptive capacity does not significantly predict BMI when controlling for DC ($\beta = 0.013$, $p = 0.498$). The indirect effect ($a \times b = 0.004$) with a bootstrapped 95% confidence interval including zero (-0.012 to 0.019) confirms the absence of mediation. Thus, H3 is rejected.

This finding misaligns with Absorptive Capacity Theory (Cohen & Levinthal, 1990; Zahra & George, 2002), which posits that firms must acquire, assimilate, transform, and exploit external knowledge to convert digital investments into innovation. It also contradicts empirical evidence from Kastelli et al. (2022), Van Hoang et al. (2025), and Miroshnychenko et al. (2021), who found that absorptive capacity mediates digital capability–innovation relationships. However, several context-specific explanations rooted in institutional theory and the nature of Liberian SMEs

explain this misalignment. First, Liberian manufacturing SMEs may leverage digital tools directly for innovation without formalized knowledge absorption processes they adopt digital solutions for immediate efficiency gains rather than strategic learning (Abubakar et al., 2019; Jonathan & Kuika Watat, 2020). Second, the study introduces the concept of digital rent: in resource-constrained environments, firms' appropriate value primarily through cost-side efficiency gains (e.g., process automation, supply chain coordination) rather than revenue-side innovation that requires complex knowledge transformation. Third, absorptive capacity may function as a moderator rather than a mediator in this context, enabling digital capability effects only when learning structures are sufficiently developed. Fourth, the cross-sectional design may fail to capture the temporal dimension of absorptive capacity, as knowledge transformation often requires time to manifest as innovation outcomes (Cohen & Levinthal, 1990). Fifth, as noted by Hervás-Oliver et al. (2021), in less innovative regions, SMEs rely more on external collaborations than internal absorptive capacity, meaning the knowledge conversion mechanism may operate through networks rather than firm-level learning processes. Thus, while Absorptive Capacity Theory assumes universal applicability, Institutional Theory explains why it fails in Liberia: weak innovation ecosystems, skill shortages, and survival priorities mean SMEs bypass formal mediation pathways and rely on direct, efficiency-oriented digital deployment.

**Table 4. Mediation Result**

| **Variable** | **Model 1** | **Model 2** | **Model 3** |
|---|---|---|---|
| | **BMI** | **AC** | **BMI** |
| Gender | 0.023 | -0.015 | 0.024 |
| | (0.036) | (0.050) | (0.036) |
| Age | 0.006 | 0.007 | 0.006 |
| | (0.014) | (0.019) | (0.014) |
| Position | -0.003 | -0.025 | -0.002 |
| | (0.016) | (0.021) | (0.016) |
| Working Experience | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |

| | | | |
|---|---|---|---|
| Education | -0.014 | -0.008 | -0.014 |
| | (0.024) | (0.033) | (0.024) |
| Size | -0.044 | 0.120*** | -0.045 |
| | (0.026) | (0.035) | (0.026) |
| DC | 0.737*** | 0.322*** | 0.733*** |
| | (0.019) | (0.025) | (0.019) |
| AC | | | 0.013 |
| | | | (0.019) |
| Constant | 0.082 | 0.232 | 0.079 |
| | (0.340) | (0.466) | (0.340) |
| $R^2$ | 0.533 | 0.124 | 0.534 |
| F | 213.04*** | 26.36*** | 189.35*** |

Note: N = 300. Unstandardized coefficients with standard errors in parentheses. Path a (DC→AC) significant; Path b (AC→BMI) non-significant (p = 0.498). Indirect effect (a×b = 0.004) with bootstrapped 95% CI [-0.012, 0.019] includes zero. H3 not supported. **p < 0.001.

### 4.5 Robustness Test

To ensure the reliability and validity of the hierarchical regression estimates, diagnostic tests for multicollinearity, heteroskedasticity, and influential outliers were conducted across all four dependent variables: value creation innovation (VCI), value proposition innovation (VPI), value delivery innovation (VDI), and value capture innovation (VCA). As shown in Table 6, multicollinearity is not a concern: the mean variance inflation factor (VIF) across all models is 1.24, with individual VIF values ranging from 1.01 to 1.95, well below the acceptable threshold of 5. This confirms that the independent variables including digital capability, leadership capability, absorptive capacity, and all controls are not excessively correlated, ensuring stable coefficient estimates. Regarding heteroskedasticity, the Breusch-Pagan and White tests confirm

homoscedastic residuals for VCI (BP = 0.10, p = 0.754; White = 66.51, p = 0.720) and VDI (BP = 0.17, p = 0.678; White = 77.03, p = 0.382). For VPI, while the Breusch-Pagan test is marginally significant (p = 0.034), the White test remains non-significant (p = 0.974), indicating no severe heteroskedasticity. For VCA, the Breusch-Pagan test shows mild heteroskedasticity (p = 0.009), but the non-significant White test (p = 0.556) suggests that any variance inconsistency is not structurally severe and does not materially threaten the reliability of the estimates. Finally, Cook's distance diagnostics reveal only one potentially influential observation per dependent variable, representing just 0.07% of the sample, which is statistically negligible and unlikely to distort the regression coefficients. Collectively, these diagnostic tests confirm that the regression assumptions are reasonably satisfied and that the estimated relationships between digital capability and the four dimensions of business model innovation are robust not driven by multicollinearity, heteroskedasticity, or influential outliers.

**Table 5. Diagnostic Test**

| DV | Mean VIF | VIF Range | Heteroskedasticity (BP$X^2$/p | White's Test $X^2$ /p | Outliers (Cook's D >4/n) |
|---|---|---|---|---|---|
| VCI | 1.24 | 1.01-1.95 | 0.10/0.754 | 66.51/0.720 | 1(0.07%) |
| VPI | 1.24 | 1.01-1.50 | 0.92/0.0339 | 52.22/0.974 | 1(0.07%) |
| VDI | 1.24 | 1.01-1.59 | 0.17/0.678 | 77.03/0.382 | 1(0.07%) |
| VCA | 1.24 | 1.01-1.95 | 6.85/0.009 | 71.64/0.556 | 1(0.07%) |

**Note:** All mean VIF values are below 2, indicating no multicollinearity concerns. Breusch-Pagan (BP) and White tests largely confirm homoscedasticity across models; although VCA shows a marginal BP result, White's test suggests no serious heteroskedasticity issue. Cook's Distance identified only one observation per dependent variable (0.07% of the sample), indicating negligible influence of outliers.

## 5. Conclusion and Implications

### 5.1 Conclusion

This study examined how digital capability drives business model innovation (BMI) in manufacturing SMEs in Liberia, a post-conflict, least developed country context, and tested whether absorptive capacity mediates this relationship. Using hierarchical regression on survey data from 300 manufacturing SMEs, the study found strong support for H1a–H1d: digital capability is positively and significantly associated with all four dimensions of BMI value creation, value proposition, value delivery, and value capture. These findings confirm that digital capability functions as a valuable, rare, and inimitable strategic resource and a higher-order dynamic capability for sensing, seizing, and reconfiguring business models. However, the study rejected H2: absorptive capacity does not mediate the relationship between digital capability and BMI. While digital capability significantly enhances absorptive capacity (path a significant), absorptive capacity does not translate into BMI (path b non-significant). This null finding, explained through institutional theory, suggests that in resource-constrained, post-conflict environments, SMEs bypass formal knowledge absorption processes and instead leverage digital tools directly for immediate efficiency gains a phenomenon this study introduces as digital rent. Thus, while digital capability directly drives multidimensional BMI, absorptive capacity does not serve as the transmission mechanism in this context, extending existing theory by specifying boundary conditions for absorptive capacity theory in least developed economies.

### 5.2 Implications

This study makes three theoretical contributions. First, it extends the resource-based view and dynamic capabilities theory by empirically demonstrating that digital capability directly drives all four dimensions of BMI in resource-constrained SMEs, confirming that digital capability constitutes a VRIN resource even in least developed country contexts. Second, it challenges the universal applicability of absorptive capacity theory by identifying a critical boundary condition: in post-conflict, institutionally weak environments, the theorized mediation pathway breaks down because firms prioritize direct, efficiency-oriented digital deployment over formalized knowledge absorption. Third, the study introduces the concept of digital rent value appropriation through cost-side efficiency gains rather than revenue-side innovation offering a new theoretical lens for

understanding digital transformation in severely resource-constrained settings where firms cannot afford exploratory learning and instead focus on immediate operational improvements.

For SME managers, the findings emphasize that investing directly in digital tools and infrastructure yields tangible innovation outcomes across value creation, proposition, delivery, and capture. Managers should prioritize digital capability development such as adopting basic digital tools for production tracking, customer engagement, and supply chain coordination rather than waiting for formal learning systems to be established. For policymakers in Liberia and similar contexts, the results suggest that supporting SME digital adoption through infrastructure investment, affordable digital tools, and basic digital literacy programs may be more immediately impactful than investing in advanced knowledge management or absorptive capacity development programs. For development partners and donor agencies, the findings indicate that interventions should focus on enabling direct digital deployment (e.g., subsidizing digital tools, providing basic digital training) rather than complex organizational learning initiatives that may not translate into innovation in resource-constrained environments.

### 5.3 Limitation and Further Studies

This study has several limitations that also inform future research directions. First, the cross-sectional design captures relationships at a single point in time, limiting causal inference and the detection of temporal dynamics; longitudinal studies are needed to examine whether absorptive capacity exerts lagged or cumulative effects on BMI over time. Second, reliance on self-reported data introduces potential common method bias, although diagnostic tests confirmed this does not materially threaten findings; future research should incorporate objective performance measures or multi-respondent designs. Third, the purposive sampling technique, while appropriate for targeting information-rich cases, limits generalizability; future studies should employ probability sampling to enhance external validity. Fourth, the focus on manufacturing SMEs in a single post-conflict, least developed country (Liberia) restricts generalizability to other sectors or contexts; comparative studies across multiple least developed countries or service SMEs are needed to determine whether the rejection of mediation is context-specific or generalizable. Fifth, the measurement of absorptive capacity focused on formal digital knowledge processes but may have missed informal learning common in SMEs; qualitative research (e.g., case studies, in-depth interviews) could uncover these informal mechanisms. Finally, future research should explore the

digital rent concept further by examining specific cost-side mechanisms (e.g., process automation, inventory optimization) through which digital capability generates value without formal mediation, and investigate potential moderators (e.g., innovation culture, institutional support) of the absorptive capacity and BMI relationship to identify conditions where absorptive capacity does translate into innovation.

## References

[1] Abubakar, A. M., Elrehail, H., Alatailat, M. A., & Elçi, A. (2019). Knowledge management, decision-making style and organizational performance. Journal of Innovation & Knowledge, 4(2), 104–114. https://doi.org/10.1016/j.jik.2017.07.003

[2] Ahmed, S. K. (2024). How to choose a sampling technique and determine sample size for research: A simplified guide for researchers. Oral Oncology Reports, 12, 100662. https://doi.org/10.1016/j.oor.2024.100662

[3] Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage Publications.

[4] Alrub, Y. A., & Sánchez-Cañizares, S. M. (2025). Dynamic capabilities and digital transformation: Toward strategic planning in the digital age Evidence from Palestine. Administrative Sciences, 15(1), 21. https://doi.org/10.3390/admsci15010021

[5] Ancillai, C., Sabatini, A., Gatti, M., & Perna, A. (2022). Digital technology and business model innovation: A systematic literature review and future research agenda. Technological Forecasting and Social Change, 188, 122307. https://doi.org/10.1016/j.techfore.2022.122307

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

[7] Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

[8] Carrasco-Carvajal, O., García-Pérez-de-Lema, D., & Castillo-Vergara, M. (2023). Impact of innovation strategy, absorptive capacity, and open innovation on SME performance: A Chilean case study. Journal of Open Innovation: Technology, Market, and Complexity, 9(2), 100065. https://doi.org/10.1016/j.joitmc.2023.100065

[9] Cohen, J. (2013). Applied multiple regression/correlation analysis for the behavioral sciences. Routledge. https://doi.org/10.4324/9780203774441

[10] Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128. https://doi.org/10.2307/2393553

[11] Creswell, J. W. (2003). Research design: Qualitative, quantitative, and mixed method approaches. Sage Publications.

[12] Diallo, A., Lim, L.-C., Wong, L.-C., & Lee, L.-W. (2023). Entrepreneurship in Liberia: challenges and opportunities of SMEs. E3S Web of Conferences, 389, 09027. https://doi.org/10.1051/e3sconf/202338909027

[13] 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. https://doi.org/10.2307/2095101

[14] Elangovan, N., & Sundaravel, E. (2021). Method of preparing a document for survey instrument validation by experts. MethodsX, 8, 101326. https://doi.org/10.1016/j.mex.2021.101326

[15] Ellström, D., Holtström, J., Berg, E., & Josefsson, C. (2022). Dynamic capabilities for digital transformation. Journal of Strategy and Management, 15(2), 272–286. https://doi.org/10.1108/JSMA-04-2021-0089

[16] Fang, T. M., Ahmad, N. H., Halim, H. A., Iqbal, Q., & Ramayah, T. (2024). Pathway towards SME competitiveness: Digital capability and digital business model innovation. Technology in Society, 79, 102728. https://doi.org/10.1016/j.techsoc.2024.102728

[17] Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation. Journal of Management, 43(1), 200–227. https://doi.org/10.1177/0149206316675927

[18] Hervás-Oliver, J.-L., Parrilli, M. D., Rodríguez-Pose, A., & Sempere-Ripoll, F. (2021). The drivers of SME innovation in the regions of the EU. Research Policy, 50(9), 104316. https://doi.org/10.1016/j.respol.2021.104316

[19] Huang, W., & Ichikohji, T. (2023). A review and analysis of the business model innovation literature. Heliyon, 9(7), e17895. https://doi.org/10.1016/j.heliyon.2023.e17895

[20] Jonathan, G. M., & Kuika Watat, J. (2020). Digital transformation and absorptive capacity in African SMEs. The Electronic Journal of Information Systems in Developing Countries, 86(4), e12133. https://doi.org/10.1002/isd2.12133

[21] Kastelli, I., Dimas, P., Stamopoulos, D., & Tsakanikas, A. (2022). Linking digital capacity to innovation performance: The mediating role of absorptive capacity. Journal of the Knowledge Economy, 15(1), 238–272. https://doi.org/10.1007/s13132-022-01092-w

[22] Kastelli, I., Dimas, P., Stamopoulos, D., & Tsakanikas, A. (2024). Linking digital capacity to innovation performance: The mediating role of absorptive capacity. Journal of the Knowledge Economy, 15(1), 238–272. https://doi.org/10.1007/s13132-022-01092-w

[23] Kumar, M. (2025). Absorptive capacity theory. In Y. Wang (Ed.), SAGE Publications, Inc. https://doi.org/10.4135/9798348830953

[24] Latifi, M., Boukamcha, F., & M'henni, H. (2021). Measuring business model innovation in SMEs. Journal of Small Business and Enterprise Development, 28(5), 721–742. https://doi.org/10.1108/JSBED-08-2020-0285

[25] Lawrence, P. R., & Lorsch, J. W. (1967). Organization and environment: Managing differentiation and integration. Harvard University Press.

[26] Mailani, D., Hulu, M. Z. T., Simamora, M. R., & Kesuma, S. A. (2024). Resource-based view theory to achieve a sustainable competitive advantage of the firm: Systematic literature review. International Journal of Entrepreneurship and Sustainability Studies, 4(1), 1–15. https://doi.org/10.31098/ijeass.v4i1.2002

[27] Merín-Rodrigáñez, J., Dasí, À., & Alegre, J. (2024). Digital transformation and firm performance in innovative SMEs: The mediating role of business model innovation. Technovation, 134, 103027. https://doi.org/10.1016/j.technovation.2024.103027

[28] Miroshnychenko, I., Strobl, A., Matzler, K., & De Massis, A. (2021). Absorptive capacity, strategic flexibility, and business model innovation: Empirical evidence from Italian SMEs. Journal of Business Research, 130, 670–682. https://doi.org/10.1016/j.jbusres.2020.02.015

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

[30] Prakasa, Y., & Jumani, Z. A. (2024). Linking digital capability to small business performance: The mediating role of digital business transformation. Cogent Business & Management, 11(1). https://doi.org/10.1080/23311975.2024.2342486

[31] Sherani, Zhang, J., Shehzad, M. U., Ali, S., & Cao, Z. (2025). Unlocking digital innovation: a moderated-mediation approach exploring the knowledge creation processes, IT-enabled capabilities and absorptive capacity in software SMEs. Business Process Management Journal, 31(1), 170–201. https://doi.org/10.1108/BPMJ-03-2024-0127

[32] Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

[33] Teece, D. J. (2025). Dynamic capabilities and related paradigms. Cambridge University Press. https://doi.org/10.1017/9781009232890

[34] Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

[35] Teoh, M. F., Ahmad, N. H., Abdul-Halim, H., & Kan, W. H. (2023). Digital business model innovation among small and medium-sized enterprises (SMEs). Global Business and Organizational Excellence, 42(6), 5–18. https://doi.org/10.1002/joe.22200

[36] Van Hoang, D., Thi Hien, N., Van Thang, H., Nguyen Truc Phuong, P., & Thi-Thuy Duong, T. (2025). Digital capabilities and sustainable competitive advantages: The case of emerging market manufacturing SMEs. SAGE Open, 15(2). https://doi.org/10.1177/21582440251329967

[37] Vaska, S., Massaro, M., Bagarotto, E. M., & Dal Mas, F. (2021). The digital transformation of business model innovation: A structured literature review. Frontiers in Psychology, 11. https://doi.org/10.3389/fpsyg.2020.539363

[38] World Bank. (2024). Liberia climate and development report.

[39] World Bank. (2025). Liberia economic update: Transforming Liberia's economy for shared prosperity.

[40] Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review, 27(2), 185. https://doi.org/10.2307/4134351