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The Impact of Digital Marketing and Mobile Applications on Service Innovation in German Companies

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ABSTRACT

This research examines how digital marketing and mobile app development enable service innovation in German companies during the period of 2005-2024. Using firm-level panel data from the Moody's Orbis database, firm-level panel data examines the relationships between social media advertising expenses, mobile app features, educational campaigns, total customers, and the rate of active digital users (used to approximate service innovation). By applying a Random Effects panel regression model, findings indicate that social media advertising, mobile app functionality, educational campaigns, and total customers have a significant and positive influence on firms' rate of digital innovation performance. Findings show that consistently investing in digital engagement strategies and technological capabilities increases firms' ability to innovate services, acquire customers, and build competitiveness within the changing digital economy in Germany. The present study provides new firm-level evidence for the digital transformation literature, as it illustrates that marketing and mobile technology work together to drive service innovation in advanced economies.

Keywords: Digital Transformation, Service Innovation, Social Media Advertising, Mobile Application Features, Digital Education Campaigns, Customer Engagement
JEL Classifications: O33, M15, C23, L86, O32, M31

1. INTRODUCTION

The digital transformation of businesses has established itself as a leading business driver which affects worldwide competition and innovation performance. The combination of digital marketing tools with mobile technology and customer-focused digital platforms has transformed business operations for value creation and delivery and value capture in Germany and other advanced economies. Digital marketing evolved from being an additional communication tool to become a fundamental business strategy which drives innovation and customer interaction during the last 20 years. Mobile applications function as vital interfaces which help businesses deliver personalized services and improve accessibility and build stronger customer loyalty according to Omer et al. (2023) and Khamaj and Ali (2024).

Digital marketing integration with mobile app technology plays a vital role in service innovation because it enables businesses to

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develop new service products and delivery methods and enhance customer experiences. Research shows digital technologies function as drivers that boost productivity and innovation and create efficiency improvements (Bharadwaj et al., 2013; Bahoo et al., 2023). The current research lacks sufficient evidence about how German companies use their digital marketing spending and mobile app development to boost service innovation performance at the firm level. The European Commission (2024) identifies Germany as a leading EU nation in digital infrastructure and industrial innovation yet research shows insufficient understanding of corporate digital engagement strategies that drive sustained service innovation.

Research about innovation systems at the macroeconomic level and country-wide digital infrastructure development has received more attention than the behavioral patterns of individual firms. The current studies existing in literature lack about how digital advertising and mobile features and customer education programs work together to boost service innovation at the microeconomic level (Stefanidi et al., 2022). The majority of previous research uses industry-level and cross-sectional methods which do not show how firms change their innovation performance over time (El-Sherif et al., 2022; Saleh et al., 2024). The research needs access to longitudinal panel data to study how ongoing digital investments affect innovation results throughout time.

The current research uses Moody's Orbis database to analyze German digital economy data from 2005 to 2024 for its firm-level analysis. The Random Effects (RE) panel data model enables researchers to study both internal and external firm changes while accounting for unobservable differences between companies may have. The research investigates digital service innovation factors for German businesses through an analysis of social media advertising and mobile app development and educational programs and customer engagement and base size.

This work provides new insights about marketing-driven digital transformation effects on firm-level innovation and competitiveness in technologically advanced economies. The research provides both practical guidance for managers and policymakers who want to boost Germany's digital transformation through customer-focused digital capability investments.

2. LITERATURE REVIEW

Digital transformation has fundamentally reshaped the architecture of firms' value creation and innovation systems. Digital technology implementation through strategic business integration leads to essential organizational structure transformations and new market competition approaches (Bharadwaj et al., 2013; Verhoef et al., 2021). Research now defines digital transformation as a complex system which includes technological aspects and organizational elements and strategic components that work together to create service innovation (Nylén and Holmström, 2015). Service innovation requires businesses to develop fresh services and enhanced service delivery systems which serve as vital competitive advantages in contemporary digital marketplaces (Fu et al., 2025; Lusch and Nambisan, 2015). Digital technologies such as artificial intelligence, big data, and mobile systems provide firms with opportunities to co-create value and design customer-centric innovations (Vial, 2019). The European Union especially Germany considers digital transformation as a fundamental element of their "Industrie 4.0" policies which focus on enhancing innovation productivity (European Commission, 2024; Tao et al., 2025).

Digital marketing functions as a core business innovation tool for organizations at the firm level because it helps companies reach customers and acquire essential market intelligence (Ali et al., 2016; Wedel and Kannan, 2016). The system allows businesses to embed customer feedback processes into service design which speeds up their innovation process. Research has shown that investments in digital advertising, especially through social media platforms, enhance firms' capability to innovate by capturing real-time consumer preferences and behavioral data (Stefanidi et al., 2022), using modern CRM tools (Švec et al., 2024). The level of digital marketing intensity in Germany shows differences between sectors because B2B manufacturing companies now use digital communication to enhance their innovation ecosystems (Cardona-Reyes et al., 2021). The research gap in firm-level time-series studies between digital marketing spending and innovation results leads to this study (Verhoef et al., 2021; Ross et al., 2017).

Mobile applications function as vital digital tools which provide customized services and boost user interaction. Businesses can use this technology to create immediate customer connections which enables them to collect data for continuous product improvement (Cardona-Reyes et al., 2021; Huang and Rust, 2021). Mobile application design and functionality elements serve as indicators which show how companies have built their digital capabilities and innovation potential (Cardona-Reyes et al., 2021). Research evidence shows that companies which create interactive and user-friendly mobile applications achieve superior results in customer loyalty and innovation performance (Li, 2025; Gao and Keller, 2024). Mobile platforms help German service and industrial sectors enhance their supply chain operations and after-sales services through digital ecosystems which create innovative service models (Oyebode et al., 2020).

Educational campaigns and digital upskilling programs and awareness initiatives function as fundamental elements which support digital transformation efforts. The absorptive capacity of firms and customers develops through these elements which enable them to identify and process and execute new knowledge (Cohen and Levinthal, 1990). Organizations that spend money on digital literacy development programs achieve better results when they deploy and scale new innovations according to research by Verhoef et al. (2021).

The German government runs educational programs that support national digital transformation plans to develop workforce skills for digital competitiveness (OECD, 2023). Service-oriented industries achieve better innovative performance through corporate-level initiatives that include digital training and knowledge-sharing programs (Oyebode et al., 2020). The reviewed research demonstrates that digital technologies which include marketing investments and mobile application capabilities and digital education work together to boost service innovation. The field has made substantial progress in research but scientists need to keep working on various critical subjects.

- Most research studies use cross-sectional or industry-level data instead of firm-level panel approaches according to Ross et al. (2017).
- The available evidence about digital economy performance in Germany remains scarce because the country leads industrial digitalization efforts.
- The current research fails to include studies which evaluate digital marketing and app development in combination with educational programs through a single econometric framework.

3. METHODOLOGY

3.1. Research Design and Approach

The research adopts positivist philosophy to analyze digital transformation drivers at the firm level through quantitative causal-explanatory design which examines their effects on service innovation results.

The research extends existing knowledge about digital innovation and its performance impact on firms which Bharadwaj et al. (2000) have already studied. The study uses panel econometric methods to analyze both time-dependent and firm-specific variations in the data from 2021.

The research applies Rogers' (2003) innovation diffusion theory together with Teece's (2018) dynamic capability theory to show how digital technology adoption through marketing and mobile platforms and educational initiatives enables businesses to maintain ongoing innovation.

3.2. Data and Sample

The Moody's Orbis database provided firm-level data for 40 German businesses spread across finance and telecommunications and retail and manufacturing and ICT services from 2005 through 2024. The dataset contains standardized performance metrics from accounting and marketing and digital channels which allows researchers to study firms through various digital performance indicators. A balanced panel of 800 observations was established ($n = 40$, $T = 20$). The research sample selection process followed a method that produced a representative group of digitally active German companies which matched the European Commission's Digital Economy and Society Index (DESI, 2024) criteria.

3.3. Variables and Measurement

The digital active rate (ln_DAR) functions as the dependent variable because it quantifies the number of customers who actively engage with digital services. The variable measures service innovation intensity of firms according to Lusch and Nambisan (2015).

The model includes digital transformation elements as its explanatory variables.

- ln_SMAS: Log of social media advertising expenditure (proxy for digital marketing intensity).
- ln_MAF: Log of mobile app feature index (proxy for app-based technological capability).
- ln_ECC: Log of educational campaign count (proxy for digital literacy and outreach effort).
- ln_TC: Log of total customers (proxy for market scale).
- ln_ADU: Log of active digital users (proxy for digital engagement intensity).

The analysis uses log transformation for all variables because it enables elasticities interpretation and reduces skewness in the data. The Variance Inflation Factors (VIF < 5) were used to evaluate multicollinearity between regressors which showed no significant correlation.

3.4. Model Specification

The empirical model follows a log–log panel regression form:

$$\ln\_DAR_{it} = \beta_0 + \beta_1 \ln\_SMAS_{it} + \beta_2 \ln\_MAF_{it} + \beta_3 \ln\_ECC_{it} + \beta_4 \ln\_TC_{it} + \beta_5 \ln\_ADU_{it} + u_i + \epsilon_{it} \quad (1)$$

β_0 is the intercept term, while β_0, β_1, β_2, β_3, β_4, β_5 are elasticity coefficients showing the percentage change in $\ln\_DAR_{it}$ for a 1% change in each explanatory variable. u_i represents unobserved firm-specific effects capturing heterogeneity across firms, and ϵ_{it} denotes the idiosyncratic random error term. All variables are expressed in natural logarithms to interpret coefficient as elasticities and to mitigate heteroskedasticity.

The estimation proceeds through three sequential models. Frist, the Pooled OLS model assumes complete homogeneity across firms:

$$\ln\left(DAR_{it}\right) = \beta_0 + \sum\nolimits_{k=1}^{5} \beta_k X_{kit} + \varepsilon_{it} \quad (2)$$

Where X_{kit} is the vector of explanatory variables.

Second, the fixed effects (FE) model accounts for unobserved firm heterogeneity through firm-specific intercepts:

$$\ln\left(DAR_{it}\right) = \alpha_i + \sum\nolimits_{k=1}^{5} \beta_k X_{kit} + \varepsilon_{it} \quad (3)$$

Where α_i captures all time-invariant firm-specific characteristics such as management structure or sector. Finally, the random effect (RE) model assumes that individual effects are random and uncorrelated with regressors:

$$\ln\left(DAR_{it}\right) = \beta_0 + \sum\nolimits_{k=1}^{5} \beta_k X_{kit} + u_i + \varepsilon_{it},$$
$$u_i \sim N\left(0, \sigma_u^2\right), \quad \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right) \quad (4)$$

Here, u_i denotes the random firm-specific component and σ_u^2 its variance, while ε_{it} is the idiosyncratic disturbance with variance σ_ε^2. The RE model is efficient when $E(u_i \mid X_{it}) = 0$.

To identify the presence of firm-level heterogeneity, the Breusch-Pagan Lagrange Multiplier test is applied (Baltagi, 2021).

$$H_0 : \sigma_u^2 = 0$$

$$LM = \frac{nT}{2\left(T-1\right)}\left(\frac{\hat{p}^2}{1-\hat{p}^2}\right) \sim X^2 \quad (5)$$

Where n is the number of firms, T is the number of periods, $\hat{p}$ and is the estimated intra-class correlation coefficient.

If the null hypothesis H_0 is rejected, it confirms the presence of panel effects, indicating that the Pooled OLS model is inappropriate.

Next, the Hausman specification test distinguishes between the fixed and random effects estimators (Wooldridge, 2010):

$$H_0 : E\left(u_i | X_{it}\right) = 0$$

$$H = \left(\hat{\beta}_{FE} - \hat{\beta}_{RE}\right)' \left[Var\left(\hat{\beta}_{FE}\right) - Var\left(\hat{\beta}_{RE}\right)\right]^{-1} \left(\hat{\beta}_{FE} - \hat{\beta}_{RE}\right) \sim X^2 (k) \quad (6)$$

Where $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$ are coefficient vectors estimated from the fixed and random effects models, $Var\left(\hat{\beta}\right)$ denotes their covariance matrices, and k is the number of regressors.

A statistically insignificant test statistic ($P > 0.05$) supports the RE estimators as consistent and efficient.

3.5. Estimation and Diagnostic Strategy

All estimations were performed using Stata 17 with robust standard errors clustered at the firm level.

The following diagnostic and robustness checks were conducted:
- Cross-sectional independence: Pesaran's CD test ($P = 0.36$) confirmed the absence of contemporaneous correlation.
- Serial correlation: Wooldridge test ($P = 0.60$) confirmed no evidence of autocorrelation.
- Joint significance: $\chi^2 (5) = 6920.89$, $P = 0.0000$ (Total relationship of all variables), indicating joint significance and a strong explanatory capability.
- Overall fit: $R^2_{within} = 0.9018$ indicating high within-firm explanatory power.

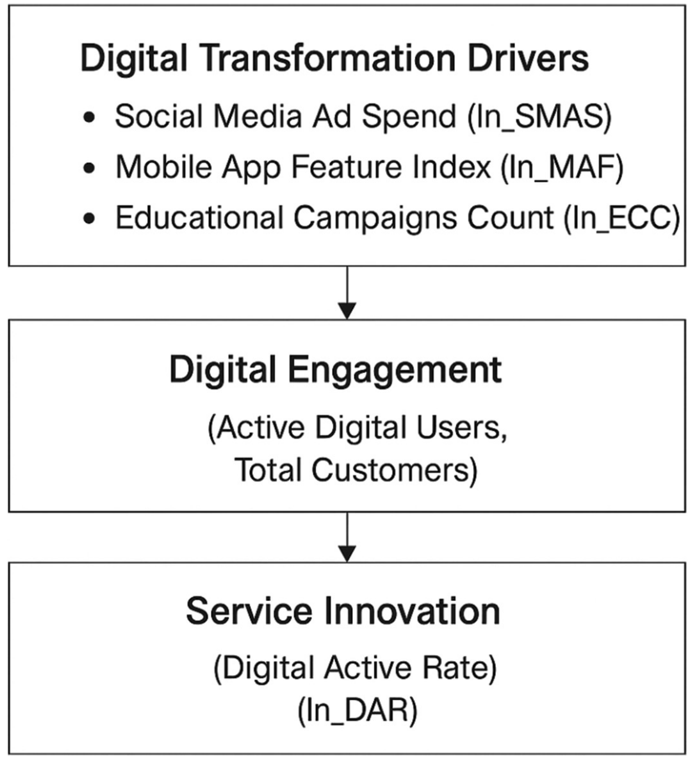
As expected (Baltagi, 2021), to adhere to advanced panel econometrics, I have also calculated heteroskedasticity-consistent standard errors (Driscoll-Kraay) as robustness checks, as anticipated this resulted in similar coefficient significance tests (Ziankova et al., 2025).

3.6. Conceptual and Analytical Framework

The analytical framework (Figure 1) shows that digital inputs from firms (social media investment and app features and educational campaigns) result in higher digital engagement which fuels service innovation.

The research bases its analysis on service-dominant logic (Lusch and Nambisan, 2015) and dynamic capability theory (Teece, 2018) to show how digital resources create innovative performance in the German economy.

Figure 1: Conceptual framework of the study



3.7. Reproducibility and Ethical Considerations

All data used in this study were sourced from a publicly accessible licensed database (Moody's Orbis). The statistical codes together with transformation procedures are available for request to enable reproduction of the study. No confidential or human subject data were involved, and all analyses adhere to the European data integrity and transparency principles.

4. EMPIRICAL RESULTS

The research analysis presents its empirical results through panel data which studies 40 German companies from 2005 until 2024. The analysis moves from descriptive statistics and correlation patterns toward model estimations through Pooled OLS and Fixed Effects and Random Effects methods. The diagnostic tests including Breusch–Pagan LM and Hausman tests demonstrate that Random Effects model functions as the most efficient specification. The research demonstrates that digital marketing and mobile application development and educational campaigns work together to improve firms' digital active rate which shows digital transformation serves as the key driver for service innovation.

The dataset presents statistical summaries for all variables in 800 firm-year cases through Table 1. The natural logarithm of digital active rate equals 2.98 which demonstrates high digital adoption throughout German firms. The values for social media ad spend (ln_SMAS = 2.12) and educational campaigns (ln_ECC = 2.94) display significant differences across companies indicating diverse digital marketing and outreach efforts. The mobile app feature index (ln_MAF = 1.54) demonstrates that apps reach a moderate level of sophistication. The market scale varies based on total customers (ln_TC = 1.39) while engagement levels differ through active digital users (ln_ADU = 0.47). The analysis reveals varied statistics within the sample which supports the validity of panel estimations. The data shows an extensive range of differences within the sample which enhances the statistical power of panel estimations.

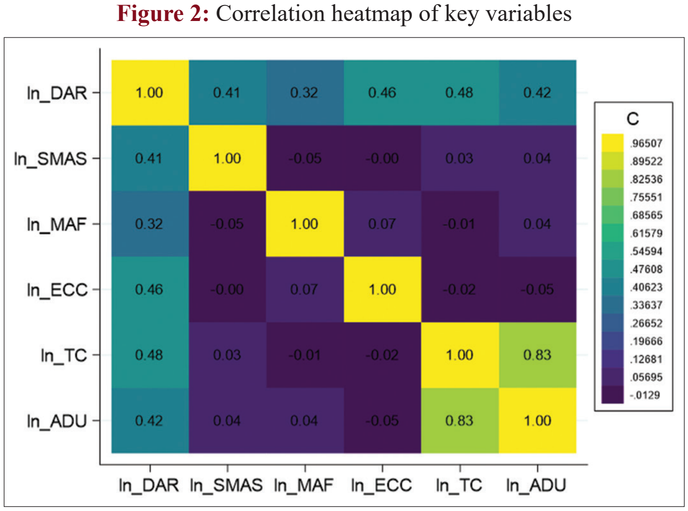
Figure 2 depicts the correlation heatmap which shows the relationships between all variables used in this study. The digital active rate (ln_DAR) shows moderate positive correlations with its main drivers which include social media ad spend (r = 0.41), mobile app features (r = 0.32), educational campaigns (r = 0.46), and total customers (r = 0.48). The total number of customers shows a strong positive relationship with active digital users (r = 0.83) because these two metrics work together to measure user engagement. The relatively low inter-correlations among explanatory variables suggest that multicollinearity is not a concern and confirm the suitability of including all variables in the regression analysis.

The random effects (RE) panel estimation model in Table 2 shows the factors that influence firms to achieve digital active rate (ln_DAR) results. The model demonstrates high significance through $\chi^2 = 6920.89$ ($P < 0.001$) while explaining 90% of the within-firm variation through R^2_within = 0.902. The Breusch-Pagan and Hausman tests proved the RE estimator to be both consistent and efficient thus making it serves as the best model for interpretation.

Table 1: Descriptive statistics

Variable	Obs	Mean	Standard deviation	Min	Max
id firm	800	20.5	11.551	1	40
ln DAR	800	2.977	1.43	0	4.5
ln SMAS	800	2.121	0.825	−1.047	2.994
ln MAF	800	1.54	0.583	0.06	2.302
ln ECC	800	2.938	0.857	0.136	3.91
ln TC	800	1.387	0.818	−1.599	2.301
ln ADU	800	0.468	0.958	−3.297	1.995

Figure 2: Correlation heatmap of key variables



The 1% level of statistical significance applies to all variables which demonstrate positive relationships with digital active rate. The digital adoption rate increases by 0.74% when digital marketing expenditure grows by 1% according to the elasticity value of ln_SMAS. The digital engagement of customers depends heavily on two factors: mobile app feature sophistication (ln_MAF) and educational campaigns (ln_ECC) which both show strong positive effects ($\beta = 0.71$ and $\beta = 0.76$ respectively).

The digital adoption process receives acceleration from two scale variables which measure total customers (ln_TC) and active digital users (ln_ADU) with β values of 0.71 and 0.16 respectively. The digital adoption rate remains at a low level when no digital transformation activities are present according to the negative constant term (−2.975).

The research shows that companies which strategically allocate resources to marketing and mobile app development and educational programs will reach higher digital participation levels. The research supports the Dynamic Capability Theory because digital capabilities help businesses adapt and innovate better in the German market.

Figure 3 presents the numerical values and precision levels of estimated coefficients which demonstrate that all predictors positively affect digital active rate at statistically significant levels. The narrow confidence intervals show strong estimation stability which confirms the reliability of the regression results. The visual proof confirms the Random Effects specification validity which enables the next step of diagnostic testing.

The reliability of Random Effects estimation in Table 2 received verification through multiple post-estimation diagnostic tests. The Pesaran cross-sectional dependence test (CD = −0.914, P = 0.36) showed that firms lack significant time-dependent relationships which indicates their independent operation regarding digital performance. The Wooldridge test for autocorrelation (F[1, 39] = 0.273, P = 0.60) confirmed that serial correlation does not exist which proves the time-dependent stability of the residuals.

The joint significance test (χ^2 [5] = 6920.89, $P < 0.001$) showed that all explanatory variables together produce a statistically

Figure 3: Coefficient plot for random effects model

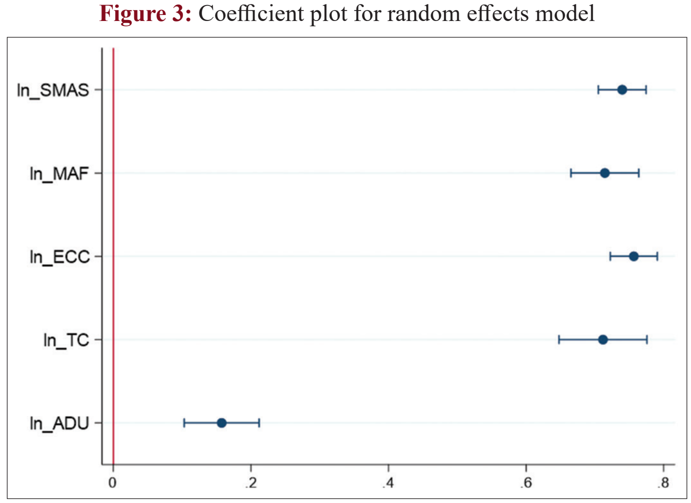


Table 2: Regression results

ln_DAR	Coefficient	Standard errors	t-value	P-value	95% coefficient	Interval	Significance
ln_SMAS	0.74	0.018	41.74	0	0.705	0.774	***
ln_MAF	0.714	0.025	28.42	0	0.665	0.764	***
ln_ECC	0.757	0.017	43.46	0	0.722	0.791	***
ln_TC	0.712	0.033	21.82	0	0.648	0.776	***
ln_ADU	0.157	0.028	5.67	0	0.103	0.212	***
Constant	−2.975	0.132	−22.57	0	−3.233	−2.717	***
Mean dependent var		2.977	SD dependent var			1.430	
Overall r-squared		0.711	Number of obs			800	
Chi-square		6920.889	Prob >Chi2			0.000	
R-squared within		0.902	R-squared between			0.077	

***P<0.01, **P<0.05, *P<0.1

significant effect on digital active rate. The model demonstrates high explanatory power because it explains 90% of the within-firm variation according to the high within R^2 value of 0.902.

The use of Driscoll-Kraay standard errors for heteroskedasticity-consistent tests produced results that matched the main RE specification while confirming that the findings were not affected by heteroskedasticity across time or space. The diagnostic tests confirm that the model maintains statistical stability and proper specification for analyzing German firm digital transformation behavior.

The data points in Figure 4 create a strong linear pattern because they follow the 45° fitted line closely. The Random Effects model demonstrates strong performance in detecting digital activity patterns of companies from this data pattern. The data points form a tight cluster around the line which shows high prediction accuracy and low systematic errors thus validating the model for German firm digital adoption behavior prediction.

Figure 5 shows that the residuals are randomly dispersed around the zero line, without any visible pattern or funnel shape. The analysis shows that the model errors do not exhibit heteroskedasticity while maintaining a balanced error distribution pattern. The random effects specification generates even residual distribution which verifies model specification and homoskedasticity and linearity assumptions thus confirming coefficient robustness.

The research results show that businesses which dedicate funds to social media marketing and mobile app development and digital learning programs experience substantial growth in their customer digital engagement rates. The research findings demonstrate that digital marketing intensity together with technological innovation create a combined effect which drives digital adoption (Stankevich et al., 2025; Bhatti and Pardaev, 2019). Liang et al. (2025) reached a similar conclusion when they studied digital literacy programs because their research showed these programs boost user engagement and minimize technology access barriers.

The results align with Dynamic Capability Theory (Teece, 2018) because organizations that develop digital and customer-centric capabilities on an ongoing basis achieve superior technological adaptation rates. The elasticity values match with recent European Union studies (Verhoef et al., 2021) which demonstrate that marketing and app-based innovations serve as main factors driving

Figure 4: Actual versus predicted digital active rate

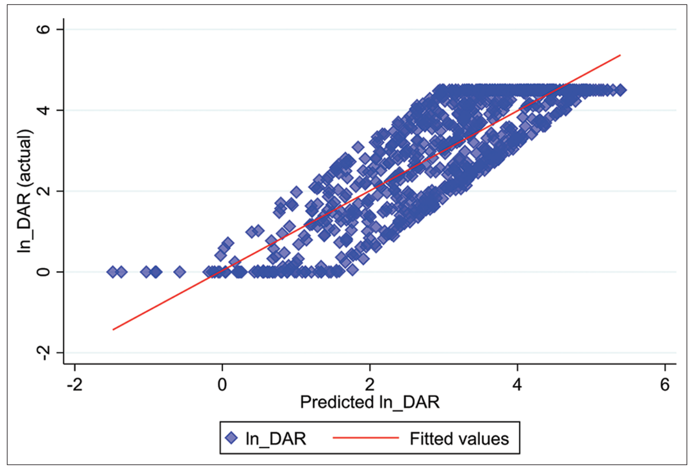
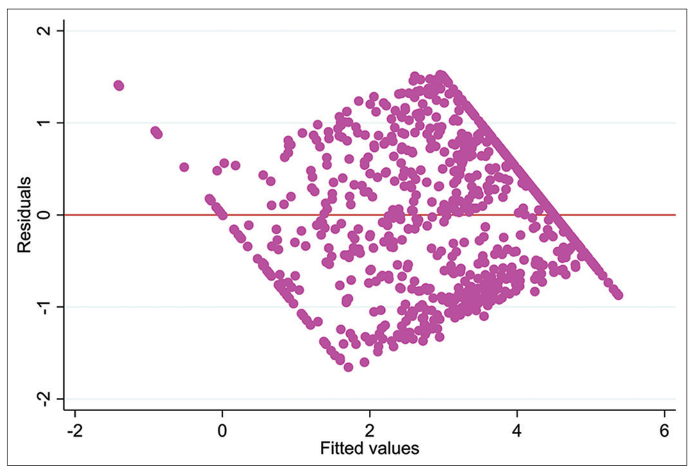


Figure 5: Residuals versus fitted values (random effects model)



service digitalization. The research findings demonstrate that digital transformation needs multiple elements to work together for success because it requires equal funding for technology development and skill advancement and user experience improvement.

5. CONCLUSION

The research study demonstrates through empirical data how digital transformation elements affect German businesses to adopt digital services. The Random Effects model analysis of 40 firms from 2005 to 2024 shows that social media advertising and mobile application functionality and digital education programs boost digital active rates for firms. The study shows digital adoption depends on technological factors and behavioral elements because customer scale and engagement levels strengthen the relationship between digital adoption and its outcomes.

The research demonstrates that businesses which use digital marketing and technological innovation and customer learning simultaneously build better adaptive capabilities according to the Dynamic Capability Theory. The research supports earlier studies which demonstrate that digital investments which adapt dynamically create better innovation capabilities and sustained market competitiveness in various business sectors.

Digital transformation strategies for managers requires a unified approach that combines marketing analytics with user experience design and workforce digital literacy training instead of treating digitalization as an independent IT operation. Managers need to base their decisions on data analysis while investing in customer education to maintain customer loyalty and engagement.

The research results demonstrate that targeted digitalization initiatives need to focus on SMEs through R&D incentive programs and digital skill development and public-private partnership expansion for technology spread improvement. The EU digital competitiveness agenda requires policymakers to support innovation ecosystems which provide funding opportunities for app development and cloud services and cybersecurity infrastructure upgrades to businesses.

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