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Unveiling the Impact of Digital Marketing on Open Innovation Performance: Fresh Insights from Tunisian Companies

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Abstract
This paper seeks to investigate the effect of digital marketing on the open innovation performance of Tunisian firms. It aims to analyze the mediating role of digital marketing among management support and innovation performance. Using Partial Least Squares-Structural Equation Modeling method for 150 Tunisian firms, the work identifies key drivers of digital transformation, such as innovation capacity, collaboration, and strategic vision, while classifying firms into digitally mature and digitally lagging groups. The results demonstrated a significant positive association between management support, the adoption of digital marketing, and open innovation performance. Additionally, the study emphasizes the non-significant moderating role of competitive intensity and the sectoral use of ICT. By offering a strategic maturity matrix, the research equips managers with actionable insights for effectively aligning digital strategies with their organizational goals, while also emphasizing the vital role of leadership in facilitating digital transformation. The results underscore the necessity for Tunisian firms to adopt digital marketing as an essential strategy to maintain competitive advantage and foster innovation.

Keywords: PLS-SEM, Digital transformation, Open innovation performance, Innovation capacity, Strategic vision

1. Introduction

Technological revolutions have indeed reshaped the economic landscape of the 21st century, mirroring the transformative impact of the industrial revolution in the 19th century. These advancements have not only unlocked unprecedented economic opportunities but have also necessitated a paradigm shift in how businesses operate and compete. The integration of cutting-edge technologies into business strategies has become a cornerstone for sustainability and survival in today’s fast-paced, digitally driven world (Brynjolfsson & McAfee, 2014; Schwab, 2017).

The transition from the agricultural and industrial eras to the knowledge era has redefined the nature of work and wealth generation. As Brynjolfsson and McAfee (2014) predicted, knowledge workers now dominate the workforce, underscoring the critical role of information and innovation in driving economic growth. This shift has compelled organizations across all sectors to undergo significant reorganizations, embracing digitalization as a core component of their strategies (Nambisan et al., 2019). Digital transformation has not only revolutionized marketing practices but has also given rise to entirely new business models, fundamentally altering the competitive landscape (Bharadwaj et al., 2013).

The strategic implications of digital transformation are profound, influencing competitive structures, operational efficiencies, and overall organizational performance. According to Verhoef et al. (2021), three key drivers; automation, dematerialization, and changes in the value chain are at the heart of this transformation. Dematerialization, in particular, has replaced traditional physical channels with digital alternatives, reducing production and transaction costs while enhancing stakeholder interactions. This shift has made digitization a survival imperative for enterprises, with a growing emphasis on the evolving role of consumers and the strategic value of data (Davenport & Ronanki, 2018).

However, the journey toward digital transformation is fraught with challenges. Organizations often grapple with a lack of vision, managerial misalignment, and resistance to change, outdated technologies, and insufficient initiative, all of which can impede progress (Kane et al., 2015). Despite these hurdles, the rise of global marketing platforms such as Amazon, Alibaba, Facebook, and Google have disrupted traditional marketing practices and redefined industry dynamics (Kumar et al., 2020). These platforms have not only altered the balance of power among industry players but have also set new benchmarks for consumer engagement and expectations.

In this rapidly evolving environment, marketing must continuously adapt to keep pace with technological advancements and shifting consumer behaviors. The acceleration of time-to-market and the demand for 24/7 consumer engagement underscore the long-term impact of digital transformation on organizations (Hinings et al., 2018). As Kumar and Rajan (2019) note, while the direct impact of digital marketing on performance is well-documented, there is limited research exploring its intermediary and mediating role between management support and organizational performance. This gap in the literature presents a significant opportunity for further exploration.

Our study seeks to address this gap by examining the mediating role of digital marketing in the association among management support and organizational performance. By integrating multiple moderating variables, we aim to provide a nuanced understanding of how digital marketing influences organizational outcomes in the context of management support. This approach aligns with recent research by Borau et al. (2021) and Kannan & Hongshuang (2021), who emphasize the importance of contextual factors in shaping the effectiveness of digital marketing strategies.

In conclusion, the ongoing digital transformation has fundamentally reshaped the business landscape, compelling organizations to rethink their strategies and operations. As technological advancements continue to drive change, the role of digital marketing as a mediator between management support and organizational performance will become increasingly critical. Future research should focus on exploring the interplay between digital marketing, technological innovation, and organizational performance, providing valuable insights for practitioners and academics alike.

2. Literature Review

Recent advancements in the application of PLS-SEM in digital marketing research have further underscored its utility in addressing complex, multidimensional constructs. For instance, studies by Hair et al. (2022) and Sarstedt et al. (2022) have demonstrated the robustness of PLS-SEM in capturing the dynamic nature of digital marketing phenomena, particularly in the context of emerging technologies such as artificial intelligence (AI) and machine learning (ML). These technologies are increasingly shaping consumer behavior and organizational strategies, necessitating advanced analytical support like PLS-SEM to model their intricate relationships (Hair et al., 2022; Richter et al., 2021).

Moreover, the integration of PLS-SEM with machine learning techniques has opened new avenues for predictive analytics in digital marketing. Shmueli et al. (2021) highlights the potential of combining PLS-SEM with predictive model assessment to enhance the explanatory and predictive power of digital marketing models. This hybrid approach allows researchers to not only test theoretical relationships but also predict future outcomes, making it particularly valuable for strategic decision-making in digital marketing (Shmueli et al., 2021; Sarstedt et al., 2022).

In addition to its methodological advantages, PLS-SEM has been increasingly applied to investigate the role of digital marketing in driving customer engagement and loyalty. Recently Kumar et al. (2021) and Hollebeek et al. (2022) examined the mediating role of digital marketing in enhancing customer experience and brand loyalty in the context of e-commerce and social media platforms. These studies emphasize the importance of digital marketing as a strategic tool for fostering long-term customer relationships in the digital age (Kumar et al., 2021; Hollebeek et al., 2022).

Furthermore, the application of PLS-SEM in cross-cultural digital marketing research has gained momentum, with recent studies by Henseler et al. (2021) and Richter et al. (2022) exploring the moderating effects of cultural dimensions on digital marketing effectiveness. These studies highlight the need for culturally sensitive digital marketing strategies and the role of PLS-SEM in uncovering nuanced insights across diverse cultural contexts (Henseler et al., 2021; Richter et al., 2022).

The inclusion of moderating variables in PLS-SEM models has also been a focal point of recent research. For example, studies by Borau et al. (2021) and Kannan & Hongshuang (2021) have examined the moderating effects of technological readiness and competitive intensity on the connection among digital marketing and organizational performance. These studies underscore the importance of considering contextual factors when analyzing the impact of digital marketing strategies (Borau et al., 2021; Kannan & Hongshuang, 2021).

In conclusion, the growing body of literature on PLS-SEM in digital marketing research highlights its versatility and robustness in addressing complex research questions. As digital marketing continues to evolve, the application of PLS-SEM, particularly in conjunction with emerging technologies and predictive analytics, will remain a critical tool for researchers and practitioners alike. Future research should continue to explore the potential of PLS-SEM in uncovering new insights into the dynamic interaction among digital marketing, technological advancements, and organizational performance (Hair et al., 2022; Shmueli et al., 2021; Sarstedt et al., 2022).

3. Research Questions and Hypotheses

The central research question guiding this study is:

What is the impact of digital marketing implementation on the open innovation performance of Tunisian firms?

To further explore this question, the following subsidiary questions are addressed:

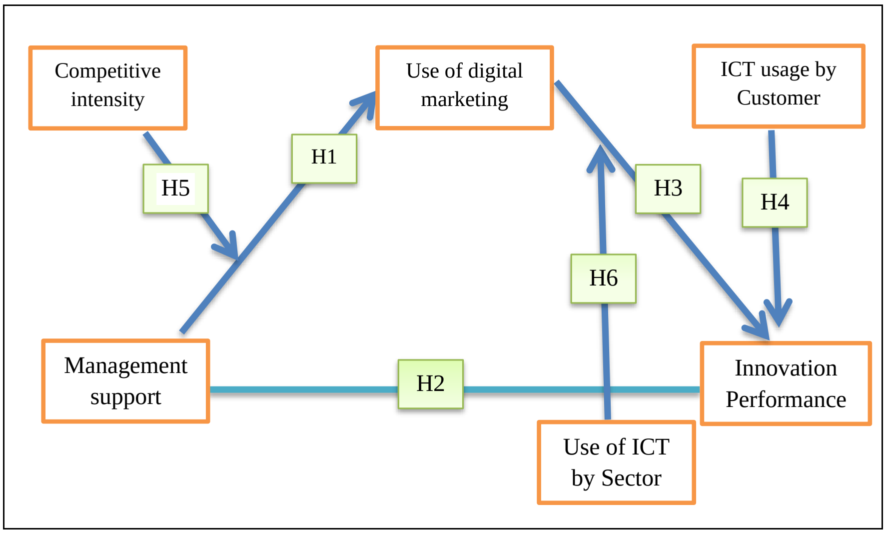
- Does digital marketing directly affect a company's open innovation performance?
- If a positive connection exists, which specific measures of open innovation performance are influenced by digital marketing?
- Does managerial support positively influence the implementation of digital marketing?
- To what extent does digital marketing serve as a mediating factor among management support and open innovation performance?
- To what extent do external factors affect or moderate the association among digital marketing and open innovation performance?
- Are there identifiable levels of digital marketing maturity among enterprises?

Based on the discussions in the empirical literature, the following hypotheses are formulated:

- *Hypothesis (H1):* There is a positive association between management support and the use of digital marketing.
- *Hypothesis (H2)*: There is a positive connection among management support and open innovation performance.
- *Hypothesis (H3)*: Digital marketing is positively correlated with open innovation performance.
- *Hypothesis (H4)*: The association between digital marketing and open innovation performance is mediated by customers` use of ICT.
- *Hypothesis (H5)*: The association between management support and the adoption of digital marketing is mediated by competitive intensity.
- *Hypothesis (H6)*: The association between digital marketing and open innovation performance is moderated by the use of ICT within a sector.

After an overview of the research method used, we detail the data collection process, analytical approach, and interpretation of the results. The research framework, illustrated in Figure 1, provides a visual representation of the relationships between the key variables, including management support, digital marketing, open innovation performance, and the moderating effects of external factors such as ICT usage by customers and competitive intensity.

Figure 1: Research framework



Source: Composed by the authors

4. Empirical Investigation and Methodology

This study uses a structural equation model to examine the mediating role of digital marketing in the connection among managerial support and open innovation performance within the Tunisian market (Brunswicker & Vanhaverbeke, 2020). The central focus of this work is the direct connection among digital marketing and open innovation performance, a finding supported by prior research (Brodie et al., 2020; Trainor et al., 2020). Additionally, we explore the less-discussed indirect relationship, where digital marketing acts as a mediating variable among managerial support and open innovation performance (Sheikh et al., 2020). Furthermore, we investigate the potential moderating role of external factors within our model.

4.1. Population, Sampling Technique, and Description

The target population for this study consists of companies across all sectors that have utilized at least one digital channel in their marketing efforts. Data were collected through a questionnaire hosted on Google Forms and distributed via two primary methods:

- The database of the Tunisian Chamber of Commerce and Industry.
- Social media platforms, specifically LinkedIn and Facebook.

Given the practical considerations of accessibility and cost, the sample is classified as a non-random convenience sample. The author's position as an elected member of the Tunisian Chamber of Commerce and Industry provided access to the organization's member database, thus streamlining the data collection process.

According to Chin & Newsted (1999), the PLS-SEM approach, which is the analytical method used in this study, can be applied with a sample size as small as 50. However, following the recommendations of Chin et al. (2003), we aimed for a sample size of 100 to 150 observations to ensure robust analysis of interaction effects involving moderating variables. The authors emphasize that the number of indicators and the reliability of items and constructs are as critical as sample size.

A total of 150 valid questionnaires were collected. The majority of respondents (89%) held executive positions, such as marketing managers, general managers, or senior executives. The service sector dominated the sample, representing 51% of respondents, followed by the industrial (23%) and commercial (25%) sectors. Small and medium-sized companies (SMEs) with fewer than 250 employees accounted for 43% of the sample, while micro-enterprises with fewer than 10 employees represented 30%. Additionally, medium-sized firms with up to 5,000 employees represented 22%, and large firms with more than 5,000 employees the remaining 5%.

4.2. Definition of Concepts and Measurement Items

Table 1 provides definitions of the key constructs based on the literature review. The measurement items were adapted from established studies (see Table 2) and operationalized using seven-point Likert scales. Before the main data collection, a pilot test involving 30 questionnaires was conducted to validate the reliability of the constructs.

All variables in the study were modeled as reflective constructs. This approach is supported by the literature, which indicates that most models in leading marketing journals employ reflective constructs (Jarvis et al., 2020). In reflective measurement theory, manifest variables (or dimensions) of a construct are highly correlated, as each reflects the underlying construct (Hair et al., 2022).

Table 1: Definition of the concepts of the study

Constructs	Previous research	Definitions
Digital Marketing	(Brodie & al, 2007 ;Adam & al 2009 ;Trainor & al, 2011 ;Olomu & Irefin, 2016).	A modern marketing practice involving the marketing of goods, services, information and ideas via the internet, email, web, mobile, networks, social...
Open innovation performance	(Gao, 2010 ;Huizingh & Zengerink, 2001)	A multidimensional process includes three dimensions: efficiency, effectiveness, and adaptability. It reflects the extent to which a firm's marketing activities contribute to both market-related objectives, like market share, revenue growth, and overall expansion, and customer-related objectives, including customer acquisition and retention.
Management support	(Brentani & Kleinschmidt., 2004)	The degree of management's positive or proactive attitude toward innovation reflects its support for new product development, particularly through the allocation of necessary resources and capital.
Customer behavior towards ICT	(Jaworski & Kohli, 1993 ; Kannan & Hong shuang, 2017)	Customer behavior toward ICT refers to the influence of the digital environment, including various web applications and digital devices, on consumers' adoption, acceptance, and use of technology.
Competitive intensity	(Porter & Miller, 1985 Zhu, Kraemer, & Xu, 2006)	The level of affectation of an enterprise by its competitors in a market, which can be modified by the adoption of new information systems.
Level of ICT use by sector	(Porter & Miller, 1985 Pilat & Wolf, 2004)	The level of ICT use by sector refers to the extent to which information and communication technologies influence industry structure, enhance data intensity across sectors, and contribute to economic growth.

Source: Composed by the authors

Table 2: The items for measuring latent variables

The construct	Measurement items (Numeric variable 1 to 7)
Digital Marketing Items borrowed and adapted from Brodie et al. (2007) and Sheikh et al. (2018)	1. Your firm employs digital marketing support, such as websites and email, to communicate and engage with consumers. 2. Your firm employs digital marketing support, such as social networks and email, to collect and address consumer feedback. 3. Your firm employs digital marketing support to support commercial activities, like price information, customer, and services.
open innovation performance Items borrowed and adapted from Brodie et al. (2007), Chavey (2010), Morgan (2012), and Trainor & al. (2011)	1. How does digital marketing impact your company's turnover? 2. How does digital marketing affect your acquisition of new customers? 3. How does digital marketing influence customer loyalty?
Top management support for digital marketing Items borrowed and adapted from: (Germann & al 2013) (Sheikh & al 2018)	1. Our senior management maintains a favorable outlook toward digital marketing. 2. Our senior management is conscious of the advantages offered by new technologies. 3. Our senior management views digital channels as strategic support for enhancing marketing activities. 4. Our senior management constantly encouraged marketing departments to utilize technological channels.
Customer behavior towards ICT (Jaworski & Kohli, 1993) (Kannan & Hongshuang, 2017)	1. Do your customers intensely use digital channels? 2. Do your customers choose to contact you via digital channels? 3. Do you agree that your customers obtain information and interact with your enterprise through digital channels?
Competitive Intensity (Porter & Miller, 1985) (Zhu, Krieger, & Xu, 2006)	1. Do you characterize the level of competition in your sector as highly intense? 2. Do you say that frequent promotional activities from competitors characterize your sector? 3. Do you consider that your sector is currently experiencing intense price competition?
Level of ICT use by sector (Porter & Miller, 1985) (Pilat & Wolf, 2004)	1. Do you think that the employ of digital technology in your sector is very intense? 2. Do you think that the use of digital is employed intensely by your competitors? 3. Do you believe that using digital technology provides a competitive advantage in your sector?

Source: Composed by the authors

5. Data analysis
5.1. The choice of the PLS approach

Structural Equation Modeling (SEM) is a second-generation multivariate analysis technique widely employed in marketing studies. It enables the testing of theoretically validated linear causal models, allowing researchers to specify how concepts are measured and how relationships between them are structured (Guarino et al., 2020). This method is particularly valuable for evaluating the relevance of theoretical models within specific contexts (Haon & Jolibert, 2020).

One of the key advantages of SEM is its ability to study latent variables, which are indirectly measured through observable variables (Haon & Jolibert, 2020). When data interpretation allows for a clear separation between predictor and response variables, partial least squares (PLS) offers a flexible approach for building statistical models to predict latent variables (Cox & Gaudard, 2020).

The PLS approach is particularly effective in handling collinear variables; those that convey similar information and is well-suited for analyzing multivariate data in marketing research. This method is ideal for both theoretical development and predictive applications, as it can confirm existing theories or identify new relationships (Fernandes et al., 2020).

Initially developed by Wold (1982, 1985), the PLS approach was introduced to address challenges in multiple linear regression models, such as multicollinearity and overparameterization. This method allows researchers to focus on addressing substantive research questions while minimizing technical limitations (Chesbrough, 2020).

Wong (2020) highlights that the PLS approach is particularly advantageous in the following scenarios:

- When the sample size is small.
- When there is a limited theoretical foundation available.
- When predictive accuracy is a primary concern.

5.2. Model Adjustment

5.2.1. Estimation Errors and Model Variable Refinement

After executing the PLS method, the SmartPLS program generated an error notice highlighting difficulties in estimating regression coefficients and correlations, particularly when matrix inversion is critical (Choi, 2020). The results revealed that such a singular matrix issue can arise due to several factors, including:

- A variable having zero variance.
- Extreme collinearity among variables.
- An insufficiently small sample size.

To address this issue, the software recommended identifying and removing the variables causing the calculation blockage.

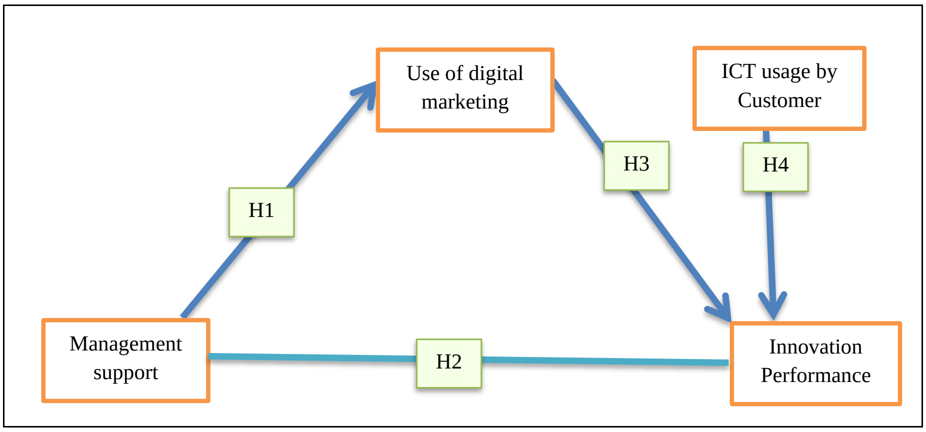
5.2.2. Purification of Variables Causing Model Calculation Errors

To resolve the calculation errors, the variables "competitive intensity" and "use of ICT in a sector" were tested for elimination. After removing these variables, the PLS algorithm executed normally, and the results for the remaining five latent variables were satisfactory.

However, during the bootstrapping process for evaluating the measurement model, the variable "use of ICT in a sector" was further eliminated, as its direct connection with marketing performance was found to be statistically insignificant. This outcome did not meet the necessary condition for conducting moderation tests (De Silva et al., 2020).

As a result, the final research model was well- fitting and met all statistical conditions after removing the two moderating variables: "use of ICT in a sector" and "competitive intensity." Figure 2 illustrates the adjusted model.

Figure 2: The adjusted model



Source: Composed by the authors

5.3. Assessment of the Measurement Model

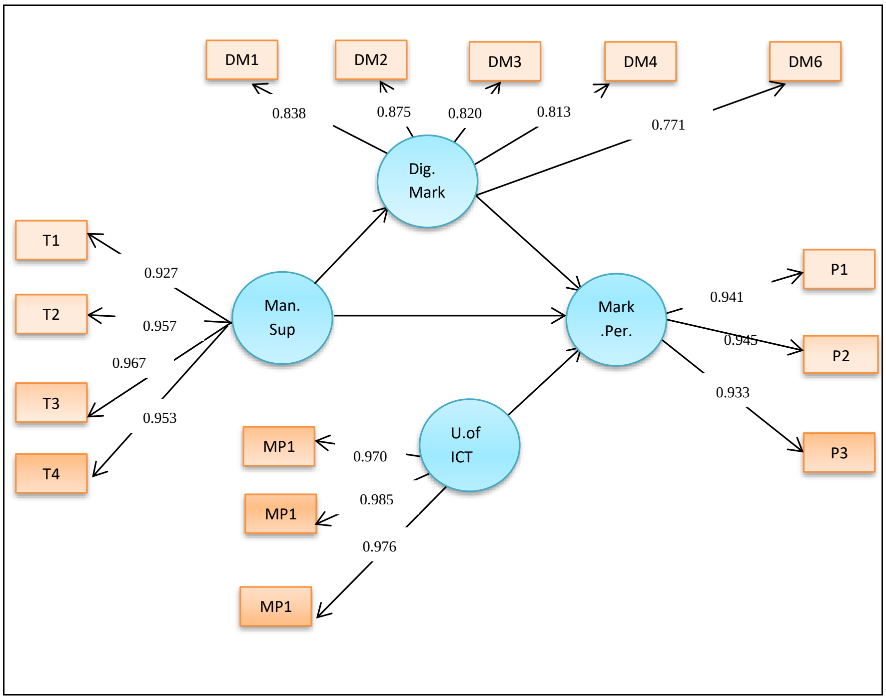
According to Fernandes (2020), the measurement model, often referred to as the external model, is assessed based on two main criteria:

Convergent Validity: Convergent validity assesses the degree to which the measures associated with a construct are consistent and reliable. Composite reliability (CR) is used as a measure of internal consistency, with a threshold value greater than 0.7 considered acceptable (Hair et al., 2022).

Discriminant Validity: Discriminant validity guarantees that each construct is distinct from others in the model. The first part is assessed employing the Fornell-Larcker criterion developed by Fornell & Larcker, (1981), which posits that a construct should exhibit greater shared variance with its indicators than with those of any other construct in the model (Hair et al., 2022). The second part of discriminant validity involves examining the degree of differentiation between constructs by analyzing cross-loadings. This step ensures that there is no significant overlap or confusion between constructs, as each indicator should load more strongly on its intended construct than on others.

The measurement scales demonstrate the reliability of the items and the convergent validity, with composite reliability values exceeding the threshold of 0.7 except for item 5 in the digital marketing construct, which recorded a value of 0.529 and was therefore excluded. The average variance extracted (AVE) ranges between 0.679 and 0.955, surpassing the minimum required value of 0.5, thereby meeting the necessary statistical conditions. Consequently, the measurement scales are deemed valid. Additionally, the digital marketing variable is explained by 50.5% of the management support variable, while the open innovation performance variable is influenced by 66.2% of the digital marketing variable, as presented in Table 3.

Figure3: Measurement model - Factor loads and coefficient values



Source: Composed by the authors

Table 4: Discriminant validity of constructs

	Digital Marketing	Open innovation performance	Management support	Use of ICT / Customers
Digital Marketing	**0.824**			
Open Innovation Performance	0.690	**0.939**		
Management support	0.710	0.730	**0.951**	
Use of ICT / Customers	0.178	0.384	0.128	**0.977**

Source: Composed by the authors

The Average Variance Extracted (AVE) for the three constructs exceeds the squared correlations between these constructs and other latent variables in the model. Based on Fornell and Larcker's (1981) criterion, we confirm the discriminant validity of all constructs within our model, as presented in Table 4.

5.4. Assessment of the Structural Model

After establishing the reliability and validity of the external models, numerous steps must be undertaken to evaluate the hypothetical association within the structural model, also referred to as the internal model (Gava et al., 2017). To address the research questions and study objectives, the PLS approach enables the measurement of direct effects based on the criteria outlined by Hair et al. (2022), as well as indirect effects, including mediation (bootstrapping-sampling) and moderation analysis.

- ✓ *Path Coefficients:* These represent the hypothetical relationships between constructs, yielding a p-value of less than 0.05. As noted by Henseler, Ringle, and Sarstedt (2014), standardized beta coefficients and path coefficients convey similar meanings in regression analysis. The resulting T-values help determine the significance of relationships. Based on the rule of thumb suggested by Hair et al. (2022), a T-value exceeding 1.64 indicates a significant relationship.
- ✓ *Multiple R^2:* This metric assesses the model's predictive capability by quantifying the contribution of each explanatory variable to the dependent variable's prediction. An R^2 value greater than 0.1 signifies a significant model, while values between 0.05 and 0.1 indicate a borderline model. If R-squared is below 0.05, the model is insignificant. Meanwhile, Chin (1998) shows that R^2 values of 0.6, 0.33, and 0.19 correspond to strong, moderate, and weak effects, respectively.

Table 5: R^2 value of endogenous latent variables

Construct relation		Result
Digital Marketing	0.505	Moderate
open innovation performance	0.662	Moderate

Source: Composed by the authors

The R^2 values for the two dependent constructs, as obtained from the SmartPLS results, fall within the range of 0.33 to 0.67. According to Chin (1998), this indicates a moderate and acceptable level of explanatory power.

- ✓ *Effect Size (F^2)*: This metric is determined by assessing the variation in R^2 when a specific construct is removed from the model. The impact of the omitted construct on a given endogenous variable is classified as follows:

0.02 represents a small effect, 0.15 a medium effect, and 0.35 a large effect.

Table 6: F² value of the exogenous latent variables

F² of the exogenous latent variables	Digital Marketing	Open innovation performance	
Digital Marketing	-	0.129	Effect Low
Management support	1.019	0.342	Significant
Use of ICT / Customers	-	0.191	Medium effect

Source: Composed by the authors

The F² values were observed to be higher than 0, indicating that each predictor contributes to explaining the dependent variable. Yet, the effect sizes vary: the digital marketing variable has a low effect, the use of ICT by customers has a medium effect, and management support has a significant effect.

- ✓ *The Stone-Geisser Coefficient (Q²) (Cross-Validation Redundancy Index):* This metric is used to evaluate the predictive relevance of the internal model and the quality of each structural equation by testing R². It involves cross-validation between the manifest variables of an endogenous latent variable and the manifest variables linked to the latent variables explaining it, based on the estimated structural model. A Q² value greater than 0 confirms the model's predictive validity.

Table 7 : Q² Values

Cross-construct redundancy	**Result**	
Open innovation performance	0.549	Significant
Digital Marketing	0.320	Significant

Source: Composed by the authors

The predictive relevance (Q²) was observed to be greater than 0, specifically 0.549 for open innovation performance and 0.320 for digital marketing. These values indicate that the model possesses predictive capability (Grigoriou & Rothaermel, 2017).

- ✓ *Goodness-of-Fit (GoF) Adjustment Index:* This index serves as an overall validation measure and is calculated as the geometric mean of the Average

Variance Extracted (AVE) and the mean R^2 of endogenous variables (Jorg & Marko, 2013). According to Wetzels et al. (2019), a GoF value above 0.25 signifies a moderate fit, while a value exceeding 0.36 indicates a strong model fit.

$$(GoF)^2 = \overline{(AVE)} * (\bar{R})^2$$

Based on Wetzels et al. (2019) and the calculated GoF value of 0.70, we conclude that the model demonstrates a sufficiently high overall validity for the PLS approach.

5.5. Direct Effect and Hypothesis Testing

To evaluate the beta values, T-values, and regression coefficients derived from the 150 responses, a total of 5,000 iterations were performed (Hair et al., 2022). Our work tests three hypotheses based on direct connection among variables. The analysis confirms the significance of these relationships, as the T-values exceed 1.64, with a particularly strong connection observed between management support and the use of digital marketing (T = 16.670).

The findings indicate that management support positively influences both the use of digital marketing and open innovation performance. Additionally, digital marketing has a positive impact on open innovation performance. Consequently, hypotheses 1, 2, and 3 are confirmed. Furthermore, the use of ICT by customers is shown to have a significant association with open innovation performance.

Table8: Direct Effect and Hypothesis Testing

hypotheses	Relationship	Std. Beta	Std. Error	T-Value	P-Value	Decision
H1	Management support -> Digital Marketing Use	0.713	0.043	16.670	0.000	Supported**
H2	Management support -> Open innovation performance	0.479	0.080	6.058	0.000	Supported**
H3	Digital Marketing Use -> Open innovation performance	0.302	0.079	3.766	0.000	Supported**
H4	ICT use / Customers -> Open innovation performance	0.268	0.049	5.476	0.000	Supported**

Source: Composed by the authors
P** < 0.01, P* < 0.05

6. Conclusion

Our research presents three key contributions:

1. Identifying Key Skills and Capacities for Digital Transformation: We outlined the essential skills and capacities required for enterprises to successfully undergo digital transformation, fostering the sustainable development of new technologies. Through a factor analysis of 150 Tunisian enterprises, we identified three critical levers: innovation capacity, collaboration capacity, and strategic vision.

Our exploratory study categorized enterprises into two groups:

- *Digitally Mature Enterprises:* These businesses possess a high level of innovation and collaboration, proactively adopt a dedicated digital strategy, and respond swiftly to digital trends. They view digital transformation as an opportunity to enhance their competitive advantage.
- *Enterprises with Weak Digital Transformation:* These companies do not prioritize digital adoption despite recognizing its potential to disrupt their sector. They acknowledge the opportunities but remain hesitant to integrate digital support into their core strategy.

By outlining these capacities and positioning enterprises within these two groups, our research provides managers with a framework to assess their organization's digital readiness. This enables them to establish the necessary foundations for a successful transformation, leveraging new support and practices such as digital marketing.

2. Empirical Validation of the Digital Marketing–Innovation Performance Link: Our second empirical study, based on a structural equation model and a survey of 150 enterprises, validated both the direct and indirect relationships between digital marketing and open innovation performance. The findings highlighted the significant role of management support in strengthening these relationships.

Additionally, our model revealed:

- A direct link between customer use of digital channels and open innovation performance.
- The non-significance of customer ICT use as a moderating factor in the connection between digital marketing and open innovation performance.

These insights help managers understand the strategic benefits of digital transformation and the central role of digital marketing in driving revenue growth, customer acquisition, and retention.

3. Classifying Enterprises by Digital Marketing Maturity: Our research identified three distinct groups of enterprises based on their digital marketing adoption and deployment levels. We proposed a *two-dimensional strategic matrix* to help managers assess their positioning as leaders, followers, or laggards in the digital marketing landscape. Depending on their position, enterprises can adopt tailored strategies to sustain, expand, or initiate performance growth.

Our findings align with Harvard Business Review (2015), which concluded that enterprises led by visionary executives who support innovation and foster internal and external collaboration are the most successful in digital transformation and outperform their competitors. However, effective deployment requires alignment between *strategy, skilled human resources, organizational culture, and technological infrastructure* to meet the digital expectations of customers, employees, and partners.

Final Considerations: The Risk of Digital Lag: Enterprises slow to adopt digital marketing risk being outpaced by more agile competitors who leverage technology to acquire, engage, and retain customers across multiple digital and physical channels.

Key questions remain for businesses aiming to thrive in a digital era:

- How can enterprises successfully navigate digital transformation?
- What skills and capacities should they develop?
- How should they position themselves in terms of digital marketing maturity?
- What strategies should they adopt to remain competitive and drive sustainable open innovation performance?

Ultimately, our research underscores that *strategic vision- not technology alone-is the driving force behind digital success.* Despite recognizing digital marketing's value, many Tunisian enterprises still treat it as an extension of traditional marketing rather than a core practice. This mirrors observations from researchers in the early 2000s. However, this digital maturity gap can be closed swiftly if enterprises implement the strategic recommendations outlined in this study.

Conflict of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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References

1. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.
2. Sarstedt, M., Hair, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2022). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, 30(1), 1-10.
3. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., & Vaithilingam, S. (2021). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 55(1), 1-20.
4. Kumar, V., Rajan, B., Gupta, S., & Dalla Pozza, I. (2021). Customer engagement in the digital age: A review and research agenda. *Journal of the Academy of Marketing Science*, 49(1), 1-25.
5. Hollebeek, L. D., Srivastava, R. K., & Chen, T. (2022). SD logic–informed customer engagement: Integrative framework, revised fundamental propositions, and application to CRM. *Journal of the Academy of Marketing Science*, 50(1), 1-20.
6. Henseler, J., Ringle, C. M., & Sarstedt, M. (2021). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, 38(1), 1-20.
7. Richter, N. F., Cepeda-Carrión, G., Roldán, J. L., & Ringle, C. M. (2022). European management research using partial least squares structural equation modeling (PLS-SEM): A review of past practices and recommendations for future applications. *European Management Journal*, 40(1), 1-15.
8. Borau, S., El Akremi, A., & Elgaaied-Gambier, L. (2021). The impact of digital marketing on consumer behavior: A PLS-SEM approach. *Journal of Business Research*, 132, 1-12.
9. Kannan, P. K., & Hongshuang, A. L. (2021). Digital marketing: A framework, review, and research agenda. *International Journal of Research in Marketing*, 38(1), 1-20.
10. Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W.W. Norton & Company.
11. Schwab, K. (2017). *The Fourth Industrial Revolution*. Crown Business.
12. Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges, and key themes. *Research Policy*, 48(8), 1-9.
13. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471-482.
14. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A

multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901.
15. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.
16. Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2015). Strategy, not technology, drives digital transformation. *MIT Sloan Management Review*, 14(1), 1-25.
17. Kumar, V., Rajan, B., Gupta, S., & Dalla Pozza, I. (2020). Customer engagement in the digital age: A review and research agenda. *Journal of the Academy of Marketing Science*, 48(1), 1-25.
18. Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, 28(1), 52-61.
19. Kumar, V., & Rajan, B. (2019). Digital marketing: A framework, review, and research agenda. *International Journal of Research in Marketing*, 36(1), 1-20.
20. Borau, S., El Akremi, A., & Elgaaied-Gambier, L. (2021). The impact of digital marketing on consumer behavior: A PLS-SEM approach. *Journal of Business Research*, 132, 1-12.
21. Kannan, P. K., & Hongshuang, A. L. (2021). Digital marketing: A framework, review, and research agenda. *International Journal of Research in Marketing*, 38(1), 1-20.