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PECULIARITIES OF DESIGN THINKING IMPLEMENTATION ON ROMANIAN COURIER INDUSTRY FROM A DYNAMIC MANAGERIAL CAPABILITY PERSPECTIVE

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Abstract

In this paper we examine the mechanisms underlying the development of dynamic managerial capability through design thinking. Using a sample of 21 lower-level managers from Romanian courier industry show that there is no statistically significant direct relationship between design thinking training and the improvement in dynamic managerial capabilities. Instead, this relationship is fully mediated by changes in genuine individual-efficacy/ genuine problem solving, latter having a stronger effect.

Keywords: design thinking, dynamic managerial capabilities genuine problem solving; genuine individual efficacy.

1. Introduction

Design thinking has become a common practice in companies as a method of problem solving and innovation [1,2]. In addition to positively influencing organizational innovation performance [3] and promoting changes in organizational mindsets and routines [4], design thinking has also been identified as a key source for developing dynamic managerial capabilities [4].

Although previous research recognizes the link between design thinking, dynamic managerial capabilities, and their impact on firm performance [2], there is still little understanding of the mechanisms underlying the development of dynamic managerial capability through design thinking. It is essential to improve our understanding of how design thinking achieves its desired outcomes, as much of the empirical research on the effects of design thinking is still anecdotal and prescriptive [5]. By deepening this understanding, we can build a

more solid and evidence-based foundation for promoting innovation within the organization [6].

The remainder of this paper is organized as follows. First, we review previous studies and develop hypotheses. Next, we introduce the methodology. Then, the data analysis and results are presented. The final section discusses the results and proposes contributions.

2. Conceptual background and hypotheses

2.1. *Dynamic managerial capabilities and design thinking training*

Dynamic managerial capabilities are managers' capabilities to build, integrate, and configure organizational assets-their resources and competences [7,8]. Dynamic capabilities refer to organizational abilities to integrate, build, and reconfigure internal and external resources and competences [7]. Dynamic managerial capabilities are a particular type of dynamic capabilities that emphasize the role that managers, individually and in teams, play in developing and executing routines in the light of new opportunities to help companies sustain and enhance their competitive advantage [8].

Design thinking is an approach to org problem solving and innovation [9] and is often chosen as an approach to address complex innovation problems and develop new offers [10,11]. As this approach entails identifying new opportunities, developing, integrating, and configuring organizational assets, most recently, scholars have suggested that there is a strong link between design thinking and dynamic capabilities both individual [4] and firm levels [2]. Design thinking practices and interactions, when performed effectively, can help managers individually and collectively to take managerial actions at different organizational levels to better sense and seize opportunities, transform organizational assets in a way that provides a source of differentiation and competitive advantage for the company [9].

Training in relevant practices and techniques is an effective way to increase managers' skills to take the desired action [12], as past research on creativity shows. Design thinking training that not only delivers information on design thinking practices but also gives participants a first-hand experience in applying design thinking practices will positively affect managers' capability to apply design thinking principles in the future and improve their dynamic managerial capabilities. In line with outlined arguments, we propose

H1. *Design thinking training will have a positive effect on managerial dynamic capabilities.*

2.2. Genuine problem solving

Genuine problem solving is a series of mental processes to identify a relevant problem, generate alternative ideas, and evaluate them [13]. Design thinking is often described as an approach to genuine problem solving [10]. It offers a way to find innovative solutions to complex problems by combining various types of thinking, seeking inspiration in unexpected places, focusing on users and involving them closely in the process, and reframing the problem from different angles [11].

Genuine problem solving as a mental process serves as a foundation for dynamic managerial capabilities, that is, successful sensing and seizing opportunities and transforming organizational assets [14]. Following these arguments, we propose:

H2. *Genuine problem solving mediates the relationship between design thinking training and dynamic managerial capabilities.*

2.3. Genuine individual-efficacy

Genuine individual-efficacy is derived from [15,16] general definition of individual-efficacy. Design thinking training helps to provide a vicarious experience or watching successful behaviour models dealing with difficult problems and demands [15]. Design thinking training emphasizes the benefits of interdisciplinary teams with complementary skill sets when solving complex challenges [16] and is therefore organized in groups. If individuals believe in their ability to produce genuine outcomes, they will enact searching for new opportunities and customers' latent needs, converting these opportunities into profitable business, and reconfiguring the necessary routines, resources, and structures for long-term success. Based on these arguments, we propose

H3. *Genuine individual-efficacy mediates the relationship between design thinking training and dynamic managerial capabilities.*

Figure 1 illustrates the theoretical research model used in this study. It comprises the hypothesized direct effect design thinking training creates on dynamic managerial capabilities and an indirect effect mediated by genuine individual-efficacy and genuine problem solving.

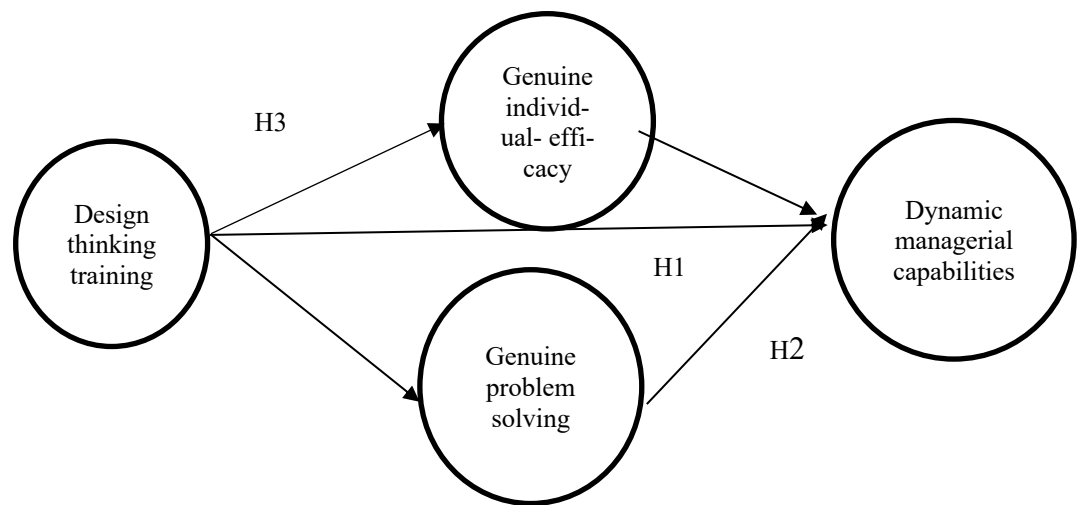


Figure 1. Theoretical research model.

3. Methodology

3.1. Research design

To test our hypotheses, we employed a field intervention with a pre-test/ post-test design and a 3-month time lag. The intervention was a two-day design thinking training, which was offered to lower-level managers of three Romanian courier companies (Posta Romana, Fan Curier and Urgent Curier). Its challenges create many opportunities for product and service innovation that managers need to be able to sense, seize and successfully implement [17], presenting a compelling empirical setting for our study. We chose a 3-month lag so that participants would have time to form habits and start new projects in their companies, which would give them the freedom to choose the approach and methods to achieve the project goals.

Trainings were organized in 3 groups of 3–9 participants, each at a different point in time from February 2024 to April 2024. Data were collected through two online surveys: one – shortly before the training, 3 months after the training. The purpose of the design thinking training was to introduce the design thinking approach with its tools through experiential learning [18]. Participants were given design challenges defined by each company that involved developing processes or product innovations. The training consisted of short theoretical inputs on tools mixed with their practical application on the given design challenges. The participants worked in cross-functional teams of 2 to 4 people.

3.2. Sample and measurement

Our sample consisted of an intervention (design thinking training) group and a control group to increase the external validity. A total of 32 lower-level managers from three companies participated in the study; 21 belonged to the intervention group and 11 to the control group. Employees could individual-select for the training if they had an opportunity to develop a new product, service, or process in their daily jobs and if they had no or only very limited knowledge about design thinking.

Both design thinking training participants and participants in the control group received pre- and post-training surveys at the same time. Participants who only filled out one of the two questionnaires were eliminated from the sample. Hence, we obtained 21 complete responses from both surveys: 11 from the intervention group and 10 from the control group, representing a 65% response rate. Participants represented different departments: operations (73%), human resources (9%), finance (9%), marketing (9%).

The variables were adapted from established multi-item reflective scales and were measured on a 5-point Likert scale (where 1=strongly disagree and 5=strongly agree). Genuine individual-efficacy was measured by three items adapted from [19]. Items assessed a person's belief in being able to generate novel ideas and come up with genuine ways to solve problems. A sample item read "I have confidence in my ability to solve problems genuinely."

Cronbach alphas for internal consistency reliabilities were .832 (pre-training) and .848 (post-training). Genuine problem solving was measured by five items adapted from [20]. Items assessed how a person approaches problem solving, that is, whether a person looks at it from different perspectives, generates multiple solutions, and uses different thinking styles. Cronbach alphas internal consistency reliabilities were .771 (pretraining) and .818 (post training). Dynamic managerial capabilities were assessed by six items adapted from [4]. Items captured sensing, seizing, and transforming capabilities. Cronbach alphas internal consistency reliabilities were .836 (pretraining) and .812 (post training).

4. Results

4.1. Exploratory factor analysis and testing hypotheses

We conducted a manipulation check to ascertain participants' knowledge of design thinking tools taught in the training. In the pre-training survey, we gave participants a list of eight tools (ethnographic methods, personas, journey maps, Brainstorming, mind mapping, prototyping techniques, field experiments,

co-creation) and asked them to check the ones they are familiar with. In the post training survey, we asked them the same question. The manipulation check was done in two out of three companies (Posta Romana and Urgent Curier). An independent sample *t* test showed the observed means of the intervention and control groups did not vary in the pre- test survey, $t(21) = .812$, $p = .419$. In the post- training survey, participants who attended design thinking training ($M = 5.46$, $SD = 1.82$) demonstrated better knowledge of design thinking tools than participants in the control group ($M = 2.28$, $SD = 1.85$), $t(21) = 5.26$, $p < .001$.

Then, we conducted an exploratory factor analysis on a data set where pre-training and post training data were combined. We obtained three factors with individual-values higher than 1. As can be seen in Table 1, the factor loadings are high enough, the variables load significantly only on one factor. For the factor analysis, all the primary factor loadings were above .601, which meet the requirements as identified by [21]. Descriptive statistics of the variables at both points of data collection and their correlations are presented in Table 2. No significant differences were found in either of the dependent variables prior to the intervention: genuine individual-efficacy and genuine problem solving (see Table 3). The intervention group had slightly higher dynamic managerial capabilities ($F(2,98) = 3.191$; $p = .077$) and had more opportunities to develop new products and services in their daily tasks ($F(2,98) = 3.609$; $p = .060$). To account for the possible effects of the opportunities to develop new products and services, we included this construct as a control variable in our model.

Finally, to test our hypotheses about the mediating role of genuine individual-efficacy and genuine problem solving, we calculated the change of each dependent variable for each participant. We then used the SPSS version 26 process and bootstrapping procedure to examine the significance of the indirect

Table 1. Exploratory factor analysis: matrix of rotated components

Item	Dynamic managerial capabilities	Genuine problem solving	Genuine individual-efficacy
I systematically identify opportunities from changes in activities of other companies	.788		
I systematically introduce changes in the ways of delivering products and services	.766		
I routinely ensure that potentially good ideas are tested	.716		
I frequently share knowledge that has the potential to influence changes on organizational routines/structures	.711		
I frequently imagine how things look from the customers' perspective	.670		
I frequently take the risk of presenting solutions	.601		

I do not limit my individual to just one way to define a problem.	.752		
I try to think about the problem from both the logical side and the intuitive side	.723		
I try to find underlying patterns among elements in the problem	.712		
I'm trying out several different alternative methods rather than relying on the same approach every time	.664		
I put questions about the nature of the problem before considering ways to solve it	.655		
I use managerial techniques to solve problems		.863	
I am a solver maker		.853	
I am good at finding original ways to solve problems		.752	
Explained variance (%)	35.801	12.71	11.401
Accumulated variance (%)	35.801	48.578	59.981

Note: Rotation method: Varimax with Kaiser Normalization. Loadings under <.350 are blended out.

effect [22]. The path (direct effect) from design thinking training to the change in dynamic managerial capabilities was not statistically significant (coeff = -.083, SE = .119, $p = .478$). The path from design thinking training to the change in genuine problem solving is positive and statistically significant (coeff = .372, SE = .133, $p = .006$). The direct effect from the change in genuine problem solving to the change in dynamic managerial capabilities was also positive and statistically significant (coeff = .298, SE = .088, $p = .001$). The path from design thinking training to the change in genuine individual-efficacy is positive and statistically significant (coeff = .242, SE = .109, $p = .026$). The direct effect from the change in genuine individual-efficacy to the change in dynamic managerial capabilities was also positive yet not statistically significant (coeff = .199, SE = .107, $p = .064$). The paths from opportunity to develop new products and services to any of the dependent variables were not statistically significant.

Table 2. Means, standard deviations, and intercorrelations

Variable	Time	M	SD	1	2	3	4	5	6	7
1 Dynamic managerial capabilities	T0	2.73	.72	.71						
2 Dynamic managerial capabilities	T1	3.04	.64	.62**	.64					
3 Genuine individual- efficacy	T0	3.61	.72	.24**	.20*	.69				
4 Genuine self- efficacy	T1	3.72	.71	.28**	.39**	.71**	.83			
5 Genuine problem solving	T0	3.59	.63	.24**	.14	.24**	.22*	.82		
6 Genuine problem solving	T1	3.70	.61	.31**	.51**	.29**	.45**	.44**	.82	

Note: $N = 21$, T0 = pretraining, T1 = post training, square root AVE in the diagonal.

**Correlation is significant at the .01 (two-tailed).

*Correlation is significant at the .05 (two-tailed).

The indirect effect was tested using nonparametric bootstrapping. If the null of 0 falls between the lower and upper bound of the 95% confidence interval, then the inference is that the population indirect effect is 0. If 0 falls outside the confidence interval, then the indirect effect is inferred to be nonzero. In this case, the indirect effect ($IE = .163$) is statistically significant at 95% $CI = (.050, .314)$. Thus, the effect of design thinking training on dynamic managerial capabilities is fully by mediated problem solving and genuine individual-efficacy, rejecting Hypothesis 1 and confirming Hypothesis 2 and 3. Figure 2 summarizes the results.

Table 3. One-way ANOVAs to validate initial equivalence between intervention and control conditions

Variable	Intervention group		Control group		F test	p value
	M	SD	M	SD		
Age	41.61	10.42	41.02	9.71	.082	.768
Opportunities	3.00	.91	2.61	.92	3.609	.058
Experience in the company	9.14	9.41	11.73	9.73	1.808	.179
Gender	1.52	.48	1.69	.44	2.439	.119
Dynamic managerial capabilities	2.88	.61	2.61	.81	3.191	.073
Genuine individual- efficiency	3.69	.74	3.60	.68	.399	.524
Genuine problem solving	3.61	.62	3.56	.63	.081	.771

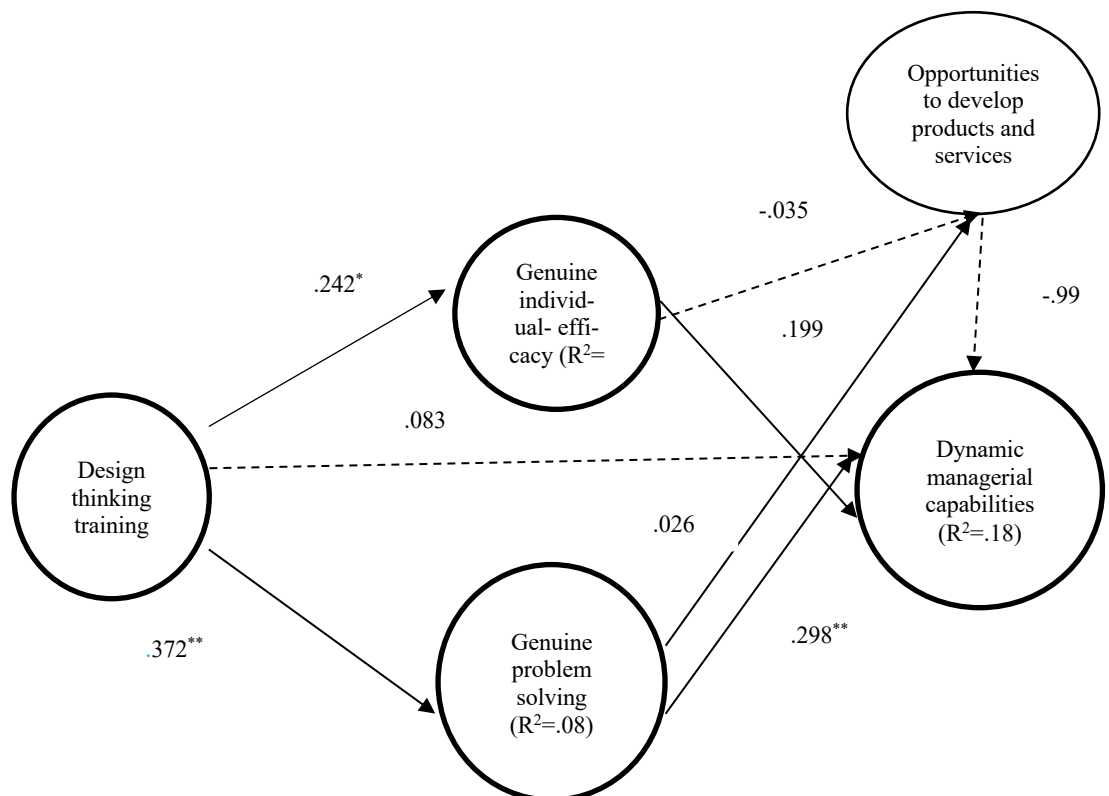


Figure 2. Model path and significant path coefficients, without controls.

5. Discussion and conclusions

The objective of this paper was to examine the mechanisms underlying the development of dynamic managerial capability through design thinking. Data from our study show that there is no statistically significant direct relationship between design thinking training and the improvement in dynamic managerial capabilities. Instead, this relationship is fully mediated by changes in genuine individual-efficacy/ genuine problem solving, latter having a stronger effect. Instead of confirming previous findings of a direct relationship between design thinking training and dynamic managerial capabilities [4], we show that this effect is rather indirect and is realized through two specific changes in managerial cognition: improved genuine problem solving as a mental process and improved genuine individual-efficacy as a psychological belief. Interestingly, the direct effect of the change in genuine individual-efficacy and the change in dynamic managerial capabilities was positive, yet not statistically significant.

REFERENCES

- [1] Bagno, R.B., Salerno, M.S., and da Silva, D.O. **Models with graphical representation for innovation management: a literature review.** *R&D Management*, 47(4), 2017, pp. 637–653.
- [2] Magistretti, S., Ardito, L., and Messeni Petruzzelli, A. **Framing the micro-foundations of design thinking as a dynamic capability for innovation: reconciling theory and practice.** *Journal of Product Innovation Management*, 38(6), 2021, pp. 645–667.
- [3] Robbins, P. and Fu, N. **Blind faith or hard evidence? Exploring the indirect performance impact of design thinking practices in R&D.** *R&D Management*, 52(4), 2022, pp. 704–719.
- [4] Kurtmollaiev, S., Pedersen, P.E., Fjuk, A., and Kvale, K. **Developing managerial dynamic capabilities: a quasi-experimental field study of the effects of design thinking training.** *Academy of Management Learning & Education*, 17(2), 2018, pp. 184–202.
- [5] Liedtka, J. **Innovation, strategy, and design: design thinking as a dynamic capability.** *Academy of Management Proceedings*, 1, 2018, 13004.
- [6] Micheli, P., Wilner, S.J.S., Bhatti, D.H., Mura, M., and Beverland, M.B. **Doing design thinking: conceptual review, synthesis, and research agenda.** *Journal of Product Innovation Management*, 36(2), 2019, pp. 124–148.

- [7] Helfat, C.E. and Martin, J.A. **Dynamic managerial capabilities: review and assessment of managerial impact on strategic change.** *Journal of Management*, 41(5), 2015, pp. 1281–1312.
- [8] Teece, D.J. **Dynamic capabilities and entrepreneurial management in large organizations: toward a theory of the (entrepreneurial) firm.** *European Economic Review*, 86, 2016, pp. 202–216.
- [9] Carlgren, L., Rauth, I., and Elmquist, M. **Framing design thinking: the concept in idea and enactment.** *Creativity and Innovation Management*, 25(1), 2016, pp. 38–57.
- [10] Brown, T. **Design thinking.** *Harvard Business Review*, 86(6), 2008, pp. 84–92.
- [11] Dell’Era, C., Magistretti, S., Cautela, C., Verganti, R., and Zurlo, F. **Four kinds of design thinking: from ideating to making, engaging, and criticizing.** *Creativity and Innovation Management*, 29(2), 2020, pp. 324–344.
- [12] Zollo, M. and Winter, S.G. **Deliberate learning and the evolution of dynamic capabilities.** *Organization Science*, 13(3), 2002, pp. 339–351.
- [13] Im, H., Hokanson, B., and Johnson, K.P. **Teaching creative thinking skills: a longitudinal study.** *Clothing and Textiles Research Journal*, 33(2), 2015, pp. 129–142.
- [14] Ferraris, A., Degbey, W.Y., Singh, S.K., Bresciani, S., Castellano, S., Fiano, F., and Couturier, J. **Microfoundations of strategic agility in emerging markets: empirical evidence of Italian MNEs in India.** *Journal of World Business*, 57(2), 2022, 101272.
- [15] Bandura, A. **Self-Efficacy: The Exercise of Control.** New York: W. H. Freeman & Company, 1997.
- [16] Jobst, B., Knöppen, E., Lindberg, T., Moritz, J., Rhinow, H., and Meinel, C. (2012) **The faith-factor in design thinking: creative confidence through education at the design thinking schools Potsdam and Stanford?** In: Plattner, H., Meinel, C., & Leifer, L. (eds), *Design Thinking Research, Understanding Innovation*. Berlin Heidelberg: Springer Verlag, pp. 35–46.
- [17] Janssen, M.J., Castaldi, C., and Alexiev, A. **Dynamic capabilities for service innovation: conceptualization and measurement.** *R&D Management*, 46(4), 2015, pp. 797–811.
- [18] Kolb, D.A. **Experiential learning: experience as the source of learning and development.** New Jersey: Prentice Hall, 1984.

TOURISM SUSTAINABLE DEVELOPMENT THROUGH BUSINESS MODEL RE-CONFIGURATION: TRADITIONAL AND DATA-DRIVEN COMPUTATIONAL INTELLIGENCE EVIDENCE FROM APULIA

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Abstract

Purpose: This study examines strategic innovation in tourism by assessing which components of business model configurations effectively predict firms' economic performance growth and sustainability over time.

Design/methodology/approach: This study develops a computational framework based on survey data to evaluate the key characteristics of firms operating in the tourism sector. Survey responses were collected and transformed into categorical and continuous variables, followed by meaningful preprocessing to reduce dimensionality and ensure analytical robustness. The set of data was then analyzed using a combination of traditional quantitative methods—such as regression and classification—and data-driven artificial intelligence approaches, with the objective of predicting firms' revenue growth and sustainability over a four-year period.

Findings: (1) The growth of tourism businesses depends on the strategic alignment of interpersonal, financial, and innovation resources within market-oriented business models. (2) Investments in technology and digitization improve

performance only when incorporated into a coherent, market-oriented strategy, while misalignment or indifference can hinder competitiveness. Sustainable tourism growth arises from business models that unite technology with social, financial, and environmental responsibility. (3) Both traditional and data-driven approaches can be successfully used for assessing the revenue growth when used as complementary strategies (rather than standalone solvers) coupled with feature reduction techniques.

Practical implications: Firms should align financial, relational, and innovation resources within a coherent, market-focused business model, strategically integrating technology to enhance performance. Banks and other decision-makers can use these insights to better assess firm capabilities, predict economic performance and sustainability, and inform investment or lending decisions.

Originality/value: The study introduces a novel integration of business model analysis with both traditional and computational intelligence methods, providing a unique approach to understanding how strategic resource alignment drives firm performance in tourism. It contributes to overcome current limitations in understanding how business models translate into measurable firm outcomes, offering both theoretical and practical insights.

Paper type: Original Paper

Keywords: Tourism competitiveness, business model, data-driven decision making, artificial intelligence, strategic innovation, tourism sustainability

1. Introduction

The contemporary business environment in the digital era is highly volatile, with rapid changes in how businesses compete, creating considerable ambiguity and significant uncertainty (Zhang-Zhang et al., 2022). These ever-changing external dynamics shape firm behaviour as they quickly react and adapt to market changes by implementing innovations across various aspects of their operations (Kamasak et al., 2016). Firms undertake innovations that involve reconfigurations in their business models (BMs), innovating and transforming the BM components that, within the new conditions and offered opportunities, can offer them a superior market position (Spieth & Schneider, 2016; Clauss,

2017), becoming the source of success and firm competitive advantage (Zott & Amit, 2007).

For management researchers, BM is a conceptual tool that reflects a business's core value proposition(s) for customers and represents a company's relevant activities in an aggregated, simplified way (Wirtz et al., 2016) and explains how an enterprise works (Magretta, 2002). Its three main dimensions of value offering, creation, and capturing (Teece, 2010) configure the value network that provides that value, and thus offers to the firm continued sustainability (Osterwalder et al., 2005; Voelpel et al., 2005). In other words, BM is a concise representation. Research recognizes the high risk that accompanies innovation of a company's BM in guaranteeing success after substantial changes (Kindström et al., 2024), failing to ensure long-term survival (Casadesus-Masanell & Zhu, 2013) and the increased rate of failure due to change resistance (Christensen et al., 2016), ambiguity related to experimentation and uncertainty for the appropriate changes to take (Demil & Lecocq, 2010). Failure often stems from managers' lack of understanding of their organizations' business models, their unique building blocks, and the potential to create a distinct competitive advantage (Zott & Amit, 2007).

In this study, we aim to address the vagueness in previous research on the relationship between BMI and firm performance. Unlike previous studies that examine average firm performance (Cucculelli & Bettinelli, 2015; Salfore et al., 2023), we address Sørensen's call (2002) to examine how new business model components affect firm performance and the nature of association between BMI and firm performance (positive or negative). This aligns with sustainability considerations and the understanding of how business model innovation supports the development of sustainability strategies (Confente et al., 2024; Rauter et al., 2017). Our empirical work focuses on small and medium-sized enterprises (SMEs) in the tourism sector, which are compelled to continually reconfigure their business models to remain competitive in the market. Given the unique characteristics of the tourism sector, this study aims to broaden our understanding of how a firm's underlying core logic and strategic choices for creating sustainable competitive advantage (Morris, Schindehutte, & Allen, 2005) and for creating and capturing value within a value network (Shafer et al., 2005; Teece, 2010) are translated into profit.

Innovating companies' BMs is both a significant managerial responsibility and a crucial capability for entrepreneurial ventures (Cosenz & Bivona, 2021; Clausen & Molden, 2024). This capability ensures companies align with evolving business conditions and emerging competitive actions in the market (Teece, 2007). Consequently, companies must reorganize their operations to meet changing customers' needs. This necessary "evolution fit" in how companies innovate their operations draws on a substantial body of research exploring

the positive relationship between business model innovation (BMI) and performance.

The literature highlights the vagueness surrounding the relationship between BMI and company performance, a complex phenomenon that depends on various contingency factors. Every firm employs a specific business model to pursue competitive advantage. However, this pursuit is complicated and sometimes unsuccessful. Idiosyncratic, company-specific reconfiguration of business model building blocks shapes firms' performance. Drawing on the business model framework and strategic management literature, we employ an innovative methodology on a sample of 270 Italian tourism SMEs. Our findings demonstrate that Apulian tourism competitiveness largely depends on strategic resource alignment: relational, financial, and responsible development are mutually achievable goals. Innovation assets can only drive growth only when they are integrated coherently and synergistically. Misaligned investments, including technological initiatives, can undermine performance and limit long-term success. This analysis highlights a path toward sustainable tourism development, demonstrating that well-coordinated investments can generate lasting economic benefits. Beyond financial gains, the observed strategic alignment is further strengthened by the growing commitment of top-performing companies to collaborations with external stakeholders, creating potential opportunities for broader community engagement and promoting environmentally responsible practices. By effectively aligning resources, tourism businesses can pursue a dual objective: improving competitiveness and promoting sustainability, demonstrating that economic growth and responsibility towards social and environmental goals are mutually reinforcing outcomes of successful tourism firms' business models.

The present paper contributes to this stream of inquiry in two ways. First, it advances systemic insights into the relationships between business model configurations and firm performance. Second, it introduces a novel methodological approach to operationalize these relationships. Specifically, it combines traditional regression models with data-driven computational intelligence techniques to predict the revenue growth of tourism firms, defined here as revenue growth in the four years preceding the COVID-19 crisis.

The analytical objective is to evaluate whether firm-level characteristics—sourced from publicly available data and survey responses—can serve as reliable predictors of economic performance. Such predictive capacity holds significant value for educators, policymakers, and practitioners. For example, financial institutions could employ these tools for credit risk assessment, bankruptcy forecasting, or optimizing lending decisions, thereby reducing operational risk through more precise performance forecasts.

To achieve this, we conducted data analysis designed around two central objectives. First, we assessed the relative contribution of individual predictors to

firm performance. Second, we tested the generalizability of our approach by partitioning the set of data into thirty training/test splits and analyzing the performance statistics across test sets. A key challenge of the set of data arises from its structure: many survey items are categorical variables with numerous features relative to the sample size. Using raw categorical data as forecasting inputs risks overfitting and inconsistency. To mitigate this and relying on the need of meaningful pre-processing operations (di Tollo et al., 2024), this contribution applies extensive preprocessing aimed at dimensionality reduction while preserving maximum informational value. Specifically, Recursive Feature Elimination (RFE), which is described in Section 3.4, has been used to reduce the predictor set to a manageable and analytically robust size.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background, followed by Section 3, which details the methodology and research context. Sections 4 and 5 present the results of the findings and discussion, respectively. Section 6 concludes the study, stating its limitations and outlining directions for future research.

2. Literature review

2.1. *Business models*

In contemporary management literature, the business model construct has been associated with the emerging 'knowledge economy' and the expansion of e-commerce (Teece, 2010: 174). Business models gained prominence in the early 1990s as a way for small enterprises to successfully compete against larger corporations globally and it has since then become a unit of analysis (Zott, Amit & Massa, 2011). Due of the multi-layered character of the notion and the multidisciplinary research in BMs (e.g., Chesbrough & Rosenbloom, 2002; Zott & Amit, 2010), the literature lacks consensus for a common BMs definition (Bigelow & Barney, 2021; George & Bock, 2011; Massa et al., 2017; Zott et al., 2011). Despite the ongoing definitional debates, the majority of accounts converge on the notion that a business model is a combination of mutually interdependent components and not a singular strategic decision and collectively define how a firm generates value for its customers, delivers that value and captures a portion of it for itself (Baden-Fuller & Mangematin, 2013; Morris, Schindehutte & Allen, 2005). Conceptualizing business models as configurations of various components (Baden-Fuller & Mangematin, 2013; Morris et al., 2005) facilitates managing factors that influence company performance (Bigelow & Barney, 2021; Lanzolla & Markides, 2021). This conceptualization underpins the concept's practical and scholarly appeal.

Among the numerous frameworks presented, Osterwalder and Pigneur's (2010) BM framework stands out as the most widely adopted and comprehensive approach. The framework comprises nine fundamental blocks, with the value proposition serving as its cornerstone. The elements essential for value creation include partnerships, activities, resources, and cost structures. Customer segments, customer relationships, distribution channels, and revenue streams define how value is delivered and potentially captured. Previous research has supported the view that business models are a set of interconnected design components that represent a company's architecture for transforming an entrepreneurial opportunity into a successful enterprise (Aversa et al., 2015; Baden-Fuller & Mangematin, 2013; Bock et al., 2021). Consequently, an established business model explains how resources and capabilities are organized within and beyond firm's boundaries. It shows how stakeholders use these resources and capabilities, how they are employed, and the rationale for the overall architecture's reliability (Amit & Zott, 2020).

Therefore, specific BM characteristics significantly influence a company's performance (Zott & Amit, 2007). If a business model is viewed as a configuration rather than a collection of independent resources, two firms with similar resources can achieve significantly different performance outcomes depending on how those resources are integrated (Miller, 1996; Zott and Amit, 2007). Superior performance is associated with business models that exhibit greater innovation and effectiveness in organizing, combining, and utilizing resources and talents in the marketplace (Sirmon et al., 2011; Zott & Amit, 2007). As Sirmon et al. (2007) and Zott (2003) explain, the dynamic process of resource management within a specific business model helps explain why companies with comparable resources and skills (and similar environmental conditions) may produce different performance outcomes. It is thus necessary to innovate the business model to maintain and strengthen this competitive advantage, as it may eventually fade (Sirmon et al., 2010; Wiggins & Ruefli, 2002).

2.2. Business model innovation and firm performance

Business Model Innovation (BMI) is central concept in entrepreneurship and strategic management. In established companies, business model innovation involves reconfiguring an existing business (Casadesus-Masanell & Zhu, 2013, Massa & Tucci, 2013). Amit and Zott (2020) define BMI as a company's strategic approach to innovating the governance, content, structure, and value logic of the business model. From this perspective, BMI offers businesses the "potential for enduring competitive advantage" by reorganizing their competencies and resources both within and outside the firm boundaries (Abrahamsson et al., 2019:77). Innovating business models is essential for

established companies and startups alike. External factors, such as the ongoing Covid-19 pandemic (Bivona & Cruz, 2021; Breier et al., 2021), intensifying competition from emerging market entrants (D'Ippolito et al., 2019; Johnson et al., 2008), evolving customer preferences (Kim & Mauborgne, 2014), the impact of new digital technologies (Urbinati et al., 2022), and sustainability demands (França et al., 2017) all contribute to its growing importance. Business model innovation encompasses developing products and services, creating new distribution channels, adopting new technologies, and forming new partnerships (Reuver et al., 2013). Notably, BMI surpasses process or product/service innovation in importance for achieving success (Amit & Zott, 2012; Johnson et al., 2008). The literature suggests that the inherent unpredictability and difficulty of altering fundamental relationships between BM components make BMI more challenging (Demil & Lecocq, 2010). Successful BMI requires modifying multiple components and outcomes depend on their interactions. This inherent unpredictability further complicates BM innovation, making it difficult to anticipate its success in advance (Andries & Debackere, 2007; Cavalcante et al., 2011; McGrath, 2010).

In BM literature, the 'sustainability' concerns the durability of competitive advantage. It ensures that a firm's profits persist rather than being competed away (Voelpel et al., 2004), aligning with the resource-orchestration account, where coherently combined resources generate value that is harder for rivals to imitate (Sirmon et al., 2011). In evaluating firm performance, meta-analyses often highlight the lack of consensus in management literature on how to define and measure business performance (Rosenbusch et al., 2013). Prior research (e.g., Rauch et al., 2009; Bilgili et al., 2017) employs diverse measures for firm performance, including sales-based metrics (such as sales growth, revenue from services, and revenue from new products), financial market indicators (such as stock market returns and Tobin's Q), and self-reported subjective assessments. The prevailing belief that BMI is essential to a company's performance (Zott et al., 2011) rests on a somewhat ambiguous and inconclusive empirical basis (Foss and Saebi, 2017; Hartmann et al., 2013; Latifi et al., 2021). Recent research has begun to question this view, suggesting that BMI may negatively impact performance (Clauss et al., 2019; Visnjic et al., 2016). The complex "paths to monetization" connecting innovation, company success, and the business model remain subject to scholarly debate (Baden-Fuller & Haefliger, 2013: 422).

2.3. *Business models in tourism*

Tourism firms encounter unique design challenges that are not generic. Most of the firms are small and family-run, often seasonal and frequently intermediated

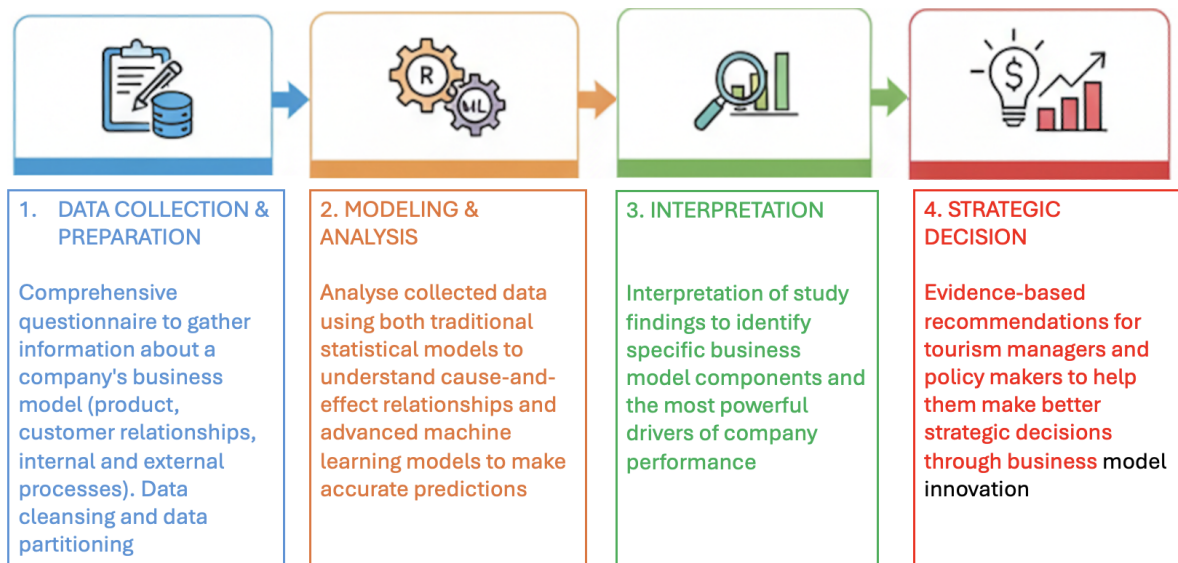
by online travel agencies, tour operators, or destination management organizations. Consequently, value is often created and captured jointly across a network of partners rather than solely by a single firm (Reinhold, Beritelli & Grünig, 2019). Historically, tourism innovation has been underthorized compared to other sectors, partly because much of it is incremental, process-level, and organizational rather than technological (Hjalager, 2010). Furthermore, typologies specifically developed for the sector distinguish product, process, managerial, marketing and institutional innovation as partially independent channels through which a tourism firm can enhance its competitive position (Camisón & Monfort-Mir, 2012). Empirical research on tourism SMEs has demonstrated a positive correlation between innovative outcomes in products and processes and profitability (Martinez-Román, Tamayo, Gamero & Romero, 2015). Additionally, Italian evidence specifically shows that productivity in the accomodation sector responds to both internal innovation investment and spill-overs from neighbouring firms (Bernini & Galli, 2023). A special issue on business model innovation in tourism and hospitality (Presenza, Petruzzelli & Natalicchio, 2019) underscores that, in this sector technology adoption, relational capital and environmental or social positioning are often discussed together rather as separate levers.

3. Method

3.1. Methodological framework

This study aims to identify and characterize the configurations of Business Model (BM) components that are most strongly associated with differences in the economic performance of tourism companies. The underlying premise is that the structure and interplay of BM components, when properly configured, constitute a key determinant of firm-level outcomes (Amit and Zott, 2011). To achieve this objective, a methodological framework was developed and is presented in Figure 1. The framework is organized into four sequential phases, each of which contributes to a comprehensive and empirically grounded assessment of BM configurations and their relationship with firm performance (Zott and Amit, 2007). The performance measure adopted in this study is revenue growth, observed over a predefined temporal horizon, which is considered a robust indicator of a company's capacity to achieve its strategic and economic objectives.

Figure 1: Methodological framework



Source: authors' processing (2024)

The first phase focuses on the development and administration of a comprehensive questionnaire designed to capture the structural and functional elements of the business models adopted by the surveyed firms. To ensure conceptual validity and comprehensive coverage, the instrument is constructed around four fundamental dimensions of BM innovation: (i) product and service development, (ii) customer relationships, (iii) internal processes, and (iv) external processes (Osterwalder and Pigneur, 2010). This dimensional structure reflects the prevailing theoretical consensus that business model innovation encompasses value creation, value delivery, and value capture mechanisms, enabling the assessment of the relative emphasis placed by firms on each of these domains (Teece, 2010). The questionnaire design follows a modular logic, allowing for the inclusion of additional dimensions or subdimensions if required by the research context. In line with established approaches in business model research, questions are formulated to stimulate critical reflection on the strategic rationale underlying each BM component, thereby enhancing the accuracy and relevance of the responses. Data collected through this instrument are systematically recorded, cleaned, and stored in a relational database. The resulting set of data is then split into data subsets to be readily usable for the next stage of training and testing predictive models.

The second phase implements inferential and predictive modeling tools to examine the relationship between BM configurations and economic performance. Two complementary classes of methods are employed. The first consisted of parametric regression models, with linear regression serving as the primary

specification. Linear regression is chosen for its interpretability and capacity to estimate the marginal effect of each BM component on the dependent variable under the assumption of a linear and additive relationship between predictors and outcome. Coefficients are estimated by minimizing a loss function, specifically the Mean Squared Error (MSE), providing both point estimates and measures of statistical significance. The second class comprised non-parametric and data-driven machine learning techniques, selected for their ability to capture nonlinear relationships, complex feature interactions, and higher-order dependencies that cannot be adequately modeled by linear methods. These techniques might include Extreme Gradient Boosting (XGBoost), K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Multilayer Perceptrons (MLPs), and ensemble learning strategies (bagging and boosting). The use of these models allows for a comparison of predictive accuracy across different methodological paradigms, highlighting the trade-off between model interpretability and predictive performance. Hyperparameter optimization, feature selection—through Recursive Feature Elimination (RFE)—and cross-validation are applied to improve model generalization and reduce the risk of overfitting.

The third phase is devoted to the interpretation of significant relationships emerging from the modeling exercises. By examining both the magnitude and direction of the estimated effects in the regression models and the feature importance scores derived from the machine learning models, this phase identifies the BM components that most strongly contributed to explain revenue growth. This stage provides crucial insights into the relative salience of different BM dimensions and their potential role as levers for improving firm performance. Finally, the fourth phase addresses the managerial and strategic implications of the findings, with particular attention to the design and governance of business model innovation processes in the tourism sector. The analysis emphasizes how the identified configurations of BM components could inform evidence-based decision-making, guide resource allocation, and support the development of policies and practices aimed at fostering competitiveness and sustainable growth within the sector.

The methodological approach integrates qualitative and quantitative research strategies to provide both explanatory and predictive insights. On the qualitative side, the study examines the BM configuration decisions made by a representative sample of tourism companies, elicited through structured, in-depth interviews. On the quantitative side, advanced analytical tools are applied to model the relationship between these BM configurations, treated as predictors, and firms' economic performance, measured through revenue variation as the outcome variable. This dual perspective enables the study to move beyond descriptive mapping of BM components, offering a rigorous assessment of their significance and relative contribution to firm performance, and providing useful

guidance to support business decision-making in the field of business model innovation.

3.2. Context: Tourism sector in the Apulian Region

To empirically apply the proposed methodological framework and evaluate its capacity to identify Business Model (BM) configurations associated with superior economic performance, the Apulia Region was selected as the reference context of analysis. Apulia constitutes one of the most dynamic and rapidly expanding tourism destinations in Italy, and as such offers a particularly suitable setting for investigating the relationship between BM configuration and firm performance. According to the Apulia Region Tourism Observatory (Osservatorio Turistico, 2024), between 2015 and 2024, the region registered remarkable growth in the tourism sector: international arrivals nearly tripled, rising from approximately 730,000 in 2015 to 2.3 million in 2024, while overnight stays increased to 7.2 million. Arrivals from abroad expanded by 228% and overnight stays by 166% in the same period, while total arrivals (domestic and international combined) grew by 72% and total overnight stays by 54%. Domestic tourism also displayed a steady upward trend, with arrivals increasing by 30% and overnight stays by 26%. Alongside this quantitative expansion, the regional tourism offering became progressively more diversified, encompassing not only seaside and coastal attractions but also its rich historical and cultural heritage, exemplified by the UNESCO-listed Trulli of Alberobello and Castel del Monte. Additional products and experiences included food and wine tourism based on local culinary traditions, active and experiential forms of tourism, and an expanding agritourism sector that valorises rural hinterland areas. This multifaceted offering, distributed across the region's six provinces, makes Apulia an ideal case for analysing heterogeneity in BM configurations and their implications for performance.

3.3. Survey design and sample

In order to operationalise the first phase of the methodological framework, a structured survey was carried out in early 2019 targeting businesses operating across the regional tourism sector. The sample comprised 270 firms, stratified to ensure representativeness of the different activities and territorial distribution within Apulia. More specifically, the survey included hotels (n=86), non-traditional accommodation providers such as agritourism establishments and bed-and-breakfasts (n=101), restaurants and catering businesses (n=29), cultural heritage and natural sites (n=12), tour operators and travel agencies (n=20),

licensed tourist guides ($n=14$), and beach resorts ($n=8$). The stratification accounted for both type of activity (accommodation versus other tourism services) and geographical distribution (province and tourist area), in order to reflect the actual composition of the tourism business fabric in the region. Data collection employed a mixed Computer-Assisted Telephone Interviewing (CATI) and Computer-Assisted Web Interviewing (CAWI) approach, thereby increasing participation rates and ensuring inclusion of firms with varying levels of digital literacy.

The survey instrument was developed in accordance with the first phase of the methodological framework (see Figure 1) and was conceptually grounded in the widely recognized Business Model Canvas (Osterwalder, 2010). Consistent with the research design, the questionnaire was structured to capture four key dimensions of business model innovation: product and service development, customer relationships, internal processes, and external processes, including partnerships and supply chain interactions. Beyond mapping BM configurations, the instrument also collected detailed data on firms' economic performance, including turnover and net income for 2015 and 2018, which enabled the calculation of revenue growth rates and facilitated benchmarking against sectoral competitors. To provide a longitudinal perspective, the questionnaire explored firms' innovation dynamics over the 2015–2018 period, examining the nature, intensity, and sources of innovation stimuli, distinguishing between internal drivers, market-induced changes, and contextual factors. Finally, respondents were asked to report on their strategic priorities and planned investment decisions, offering insight into their future orientation and their propensity to engage in further business model innovation. A complete version of the questionnaire is provided in Appendix 1, while Figure 2 presents the detailed mapping of each question to the BM components and innovation dimensions investigated.

Figure 2: Mapping questionnaire to BM components

	Questions									
	2.1	3.2	3.3		2.2.	1.6	3.1	4.2	4.3	4.4
Innovation types				Different innovation stimuli						
product and service development	2.1.1	3.2.1	3.3.1		2.2.1					
	2.1.2	3.2.2	3.3.2		2.2.2					
	2.1.3	3.2.3			2.2.3					
customer relationships	2.1.4	3.2.4	3.3.3		2.2.6					
	2.1.5	3.2.5			2.2.4					
	2.1.6				2.2.5					

	Questions									
	2.1	3.2	3.3		2.2.	1.6	3.1	4.2	4.3	4.4
	2.1.7	3.2.6	3.3.4		2.2.7					
	2.1.8				2.2.8					
	2.1.9				2.2.9					
internal processes	2.1.10	3.2.7	3.3.5		2.2.1 0					
	2.1.11	3.2.8	3.3.6		2.2.1 1					
			3.3.8	Firm's performance						
			3.3.9			1.6.1	3.1.1			
			3.3.10			1.6.2	3.1.2			
	2.1.12	3.2.7	3.3.6			1.6.3				
	2.1.14					1.6.4				
external processes	2.1.13	3.2.9	3.3.7	Effects on the external environment						
	2.1.15	3.2.10	3.3.9			1.6.5				
	2.1.16		3.3.10			1.6.3		4.2.1	4.3.1	4.4.1
	2.1.17					1.6.5		4.3.2	4.4.2	
	2.1.18								4.4.3	
	2.1.19								4.4.4	
									4.4.5	
									4.4.6	
									4.4.7	

3.4. Data analysis

The survey concluded in February 2019, and the collected responses were subsequently digitised, validated, and consolidated into a shared database for analysis. Data cleaning procedures were applied to ensure completeness, consistency, and plausibility of responses, while quantitative indicators were standardised to allow for comparison across firms of different sizes. The set of data was then prepared for the modelling phase, including the partitioning of observations into training and test subsets, in line with the methodological framework. This step ensured the robustness of subsequent empirical analyses by enabling both in-sample estimation and out-of-sample validation. The case study of Apulia thus provides not only a rich empirical basis for the application of regression-based and machine learning approaches, but also a highly dynamic and diverse context in which to explore how BM configurations contribute to differences in firms' ability to achieve revenue growth.

This section presents the data analysis conducted to evaluate the relationship between revenue growth and a set of predictors describing the main features of firms in the set of data. As outlined in the Introduction, the analysis proceeded in two stages. First, we applied computational methods to the entire set of data to assess the relative contribution of each predictor to the outcome. Second, we evaluated the generalisation capability of our models—i.e., their ability to operate on previously unseen data—by partitioning the set of data into 30 different train/test splits and analysing performance statistics on the corresponding test sets.

The set of data consists of 270 observations and 119 features, which introduces challenges typical of high-dimensional and unbalanced data. Such conditions increase the risk of overfitting and overparameterization, potentially leading to artificially inflated measures of model fit, such as high R-squared values. To address these issues, we implemented a data preprocessing phase, consistent with recommendations in Corazza et al. (2021).

Specifically, we employed Recursive Feature Elimination (RFE) (Guyon, Weston, Barnhill & Vapnik, 2002), a widely used technique for feature selection. RFE iteratively trains a model on the full set of predictors, ranks features by importance, and progressively removes the least relevant variables until a predefined number n of features is retained (Brzezinski, 2020; Naseriparsa, Bidgoli, & Varaei, 2014). This procedure reduces noise, mitigates overfitting, and improves interpretability by focusing on the most informative subset of predictors. To determine the optimal number of retained features, we used the F-Race procedure (Yuan, Stützle, & Birattari, 2010), which identified $n = 30$ as the most effective subset size. For the base estimator in RFE, we selected a Random Forest Regressor, chosen for its robustness and capacity to capture non-linear patterns in complex sets of data (Xia & Yang, 2023; Pardeshi & Patil, 2023).

4. Findings

4.1. Analysis on the full set of data

Regression analysis (Kiefer & Wolfowitz, 1959) represents a statistical process in which a set of input attributes (i.e., predictors) is employed to approximate a continuous numerical outcome for another attribute. In the present study, we applied linear regression, which assumes a linear relationship between the input features and the target variable, to model the association between the dependent variable—namely, revenue growth variation—and the features of a given business (i.e., independent variables or predictors). This is achieved by fitting a straight line (or, more generally, a hyperplane in higher dimensions) that minimises the error, understood as the distance between the predicted

values (i.e., points on the regression line corresponding to the predictor values) and the actual observations.

During training, the coefficients of the predictors are estimated by minimising a loss function, typically the Mean Squared Error (MSE), defined as the average of the squared distances (errors) between predicted and actual values. The objectives of this first analysis were twofold: (i) to assess whether it is possible to predict revenue growth variation through linear regression, and (ii) to evaluate which predictors are statistically significant in this context.

To address the first objective, we computed the R-squared of the regression, together with the adjusted R-squared, which controls for the number of predictors included in the model. In addition, we considered the value of the F-statistic, which tests the overall significance of the regression by comparing the explained variance to the unexplained variance (Camatti et al., 2024), alongside its corresponding p-value, which represents the probability of obtaining an F-statistic greater than the observed one under the null hypothesis of no explanatory power. Results are reported in Table 1 (column a).

Table 1: Estimates of linear regression to predict revenue growth variation (a) and to classify revenue variation, i.e., improve, worsen, or stay stable (b): significance statistics.

	Linear (a)	MNL (b)
R-squared	0.61	0.85
Adjusted R-squared	0.60	0.84
F-statistic	51.87	25.40
P-value of the F-test	<0.01	<0.01

The analysis yielded a small p-value, which confirms the statistical significance of the regression model. Moreover, the R-squared values, which were positive and greater than 0.5, indicate a reasonable—though improvable—fit. Regarding the assessment of predictor significance, we identified several predictors with p-values below the 0.05 threshold (see Table 2, columns “Linear”; results for the entire database, including non-significant ones, are available upon request).

Table 2: p-values of significant predictors found when using Linear (for prediction) and MNL (for classification). Only predictors whose p-values are smaller than 0,05

are reported, along with the correspondent coefficient. Label “see text” indicates that the information about the coefficients is to be found in the main text.

Question	Linear	MNL	coeff.	Question	Linear	MNL	coeff.	Question	Linear	MNL	coeff.
S1Q062	0.023	<0.001	12,783	S2Q01_a_201804	0.305	<0.001	-0,115	S2Q02_06	0.047	0.644	0,366
S1Q063	0.042	0.209	9,133	S2Q01_a_201509	0.003	0.127	-0,304	S2Q02_07	0.404	0.022	-0,083
S1Q072	<0.001	0.384	-0,676	S2Q01_a_201809	0.507	0.017	0,001	S3Q01_20152	0.226	0.012	-2,010
S1Q081	<0.0001	0.420	0,133	S2Q01_b_201813	0.401	0.036	0,057	S3Q02_05	0.027	0.023	see text
S1Q09_b	0.023	0.504	-0,074	S2Q01_b_201815	0.001	0.286	0,496	S3Q02_08	0.038	0.245	-1,644
S2Q01_a_201501	0.129	0.036	-0,819	S2Q01_b_201515	0.042	0.466	0,958	S4Q023	0.025	0.617	-0,796
S2Q01_a_201801	0.242	0.008	-1,458	S2Q01_b_201816	0.005	0.789	0,052	S4Q051	0.046	0.767	-1,033
S2Q01_a_201504	0.004	0.189	-0,139	S2Q01_b_201517	0.156	0.017	0,042	S5Q05_b22	<0.0001	0.045	see text

Examining the signs of the associated regression coefficients (for the linear case) provides valuable insights into the mechanisms shaping firm performance. In particular, results highlight the role of business model components explicitly declared by the firms themselves (Question series S 2.1), as well as other factors that companies directly recognize as critical to their success. Furthermore, predictors associated with the interest in, and effective use of new technologies emerge as particularly influential. Among the most relevant success factors are accessibility to potential customers, the efficient management of business processes, and investments in digital infrastructure and the digitalisation of management practices.

Table 3 shows a grouping of questions found to be predictive of revenue performance, along with an explanation of the corresponding business model component represented. Nevertheless, as stated in the Introduction, the ultimate aim of our work is not limited to assessing linear relationships, but rather to develop a predictive tool capable of classifying changes in revenue growth variation. More specifically, we seek to construct a model which, given the characteristics of a firm, can predict whether revenue will improve, worsen, or remain stable. This naturally leads to a classification exercise (Clancey, 1984) in which a set of input attributes (predictors) is used to determine the class membership of an object by partitioning the multi-dimensional feature space into distinct regions corresponding to different classes, and subsequently assigning each object to its appropriate class.

Table 3: Business model components and their relationship with revenue performance

Question Code	Question (from questionnaire)	Question objective	Linear p	MNL p	Relationship sign
S1Q062	1.6 Trend of average revenue	Outcome (proxy of performance measure)	0.023	<0.001	+
S1Q063	1.6 Trend of the number of seasonal employees	Firm profile (performance-adjacent)	0.042	0.209	+
S1Q072	1.7 Average number of seasonal employees (2018)	Firm profile (control variable)	<0.001	0.384	-
S1Q081	1.8 Percentage of turnover from Italian clients	Firm profile (control variable)	<0.0001	0.420	+
S1Q09_b	1.9b Revenue class (2018)	Outcome (proxy of performance measure)	0.023	0.504	-
S2Q01_a_201501	2.1 Importance of technological content of the service (2015)	Technology (BM component)	0.129	0.036	-
S2Q01_a_201801	2.1 Importance of technological content of the service (2018)	Technology (BM component)	0.242	0.008	-
S2Q01_a_201504	2.1 Importance of customer acquisition processes (2015)	Market orientation (BM component)	0.004	0.189	-
S2Q01_a_201804	2.1 Importance of customer acquisition processes (2018)	Market orientation (BM component)	0.305	<0.001	-
S2Q01_a_201509	2.1 Importance of CRM systems (2015)	Technology/ Relational (BM component)	0.003	0.127	-
S2Q01_a_201809	2.1 Importance of CRM systems (2018)	Technology/ Relational (BM component)	0.507	0.017	+
S2Q01_b_201813	2.1 Importance of relationships with suppliers (2018)	Relational (BM component)	0.401	0.036	+
S2Q01_b_201515	2.1 Importance of access to finance for new investment (2015)	Financial (BM component)	0.042	0.466	+
S2Q01_b_201815	2.1 Importance of access to finance for new investment (2018)	Financial (BM component)	0.001	0.286	+
S2Q01_b_201816	2.1 Importance of partnerships with firms in the same sector (2018)	Relational (BM component)	0.005	0.789	+

S2Q01_b_201517	2.1 Importance of partnerships with firms in other sectors (2015)	Relational (BM component)	0.156	0.017	+
S2Q02_06	2.2 Deterioration of results as a stimulus for innovation	Adaptive orientation (BM component)	0.047	0.644	+
S2Q02_07	2.2 Customer demands as a stimulus for innovation	Adaptive to market (BM component)	0.404	0.022	–
S3Q01_20152	3.1 Belief that 2015 average profit exceeded competitors' profit	Outcome-adjacent belief (performance measure)	0.226	0.012	–
S3Q02_05	3.2 Belief that customer accessibility is a success factor	Market orientation (BM component)	0.027	0.023	+
S3Q02_08	3.2 Belief that management of business processes is a success factor	Internal process (BM component)	0.038	0.245	–
S4Q023	4.2 Availability of technology and digital infrastructure	Technology (BM component)	0.025	0.617	–
S4Q051	4.5 Investment in digitalisation of management processes	Technology (BM component)	0.046	0.767	–
S5Q05_b22	5.5 Availability of conference facilities	Product/market diversification (BM component)	<0.0001	0.045	+

To this end, we employed Multinomial Logistic Regression (MNL), an extension of logistic regression that generalises the binary case to settings involving more than two possible outcomes. MNL estimates the probability of each class by modelling the relationship between the predictors and the log-odds of the various possible outcomes. During training, the algorithm simultaneously fits multiple logistic regression models, each comparing one class against a designated baseline class, and assigns as final output the class with the highest predicted probability. It is worth noting, however, that the performance of Multinomial Logistic Regression can decline when applied to highly complex sets of data or in the presence of strongly non-linear patterns.

The results of the classification analysis are reported in Table 1 (column b). At first inspection, it is evident that the R-squared values associated with the classification exercise are higher than those obtained in the linear regression case, thereby suggesting stronger explanatory power. Nonetheless, both models—

regression and classification—are statistically significant, as confirmed by their associated p-values. As for the assessment of the significance of the predictors, our analysis suggests that while historical focus on technology and internal customer processes was insufficient on its own, companies that integrated relational, financial, and market-oriented strategies—particularly in more recent years—were better positioned to achieve the highest turnover. Success, therefore, depends less on isolated innovations and more on the strategic alignment of resources, relationships, and adaptive market awareness.

As a final observation, the application of linear and MNL methods identifies significant predictors that differ when considering the two forecasting exercises. The only significant predictors for both exercises are associated with questions S3Q02_05 and S5Q05_b22, further highlighting how companies that prioritize making their services and offerings easily available are better positioned to attract new customers and ultimately improve financial performance. As for the sign of the coefficient, S3Q02_05 shows a positive coefficient for both linear and MNL approaches (with value close to 0.02 in both cases).

4.2. Analysis over different train/test partitions

As stated in the Introduction, this research also aims to evaluate whether our approach can predict the sign of revenue growth variation based on business features. This prediction can be achieved using either model-driven approaches, which assume a predefined data model, or data-driven AI approaches. In addition to the previously described Multinomial Logit (MNL) model, we have employed the following machine learning algorithms:

Extreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016) is an optimized implementation of gradient-boosted decision trees. XGBoost builds an ensemble of decision trees sequentially, with each new tree trained to fit the negative gradient (i.e., the pseudo-residual) of the prediction errors from the existing ensemble. The outputs (weights) of the tree leaves are scaled by a learning rate and added to the ensemble iteratively until a predefined number of trees is reached. XGBoost supports sample weighting, which balances biased sets of data, penalizes misclassifications, and addresses minority classes. These characteristics make it particularly suitable for imbalanced sets of data while enhancing both accuracy and robustness.

K-Nearest Neighbours (KNN) (Guo et al, 2003) is a non-parametric algorithm applicable to both classification and regression tasks. For classification, KNN assigns the most common class among the k nearest neighbors, whereas for regression, it predicts the average (or weighted average) of the neighboring values. KNN is simple and interpretable; however, its performance deteriorates in high-dimensional feature spaces due to the “curse of dimensionality.”

Support Vector Machine (SVM) (Cortes & Vapnik, 1995) aims to identify the optimal hyperplane that separates data points of different classes with the maximum margin. For non-linearly separable data, SVM employs kernel functions (e.g., linear, polynomial, or radial basis functions) to project data into a higher-dimensional space where a linear separation becomes possible. During training, only a subset of data points, called support vectors, determines the hyperplane position.

Multilayer Perceptrons (MLPs) (Rosenblatt, 1958) are neural networks capable of modeling complex, non-linear relationships. An MLP consists of an input layer, one or more hidden layers, and an output layer, with each layer containing neurons that perform linear transformations (weighted sums plus biases) followed by non-linear activation functions, such as ReLU or SoftMax. MLPs are trained using backpropagation and gradient descent, iteratively updating weights and biases to minimize a loss function (e.g., binary cross-entropy or log loss). In our experiments, we implemented a standard MLP combined with Recursive Feature Elimination (RFE), which reduces the feature space, and ensemble training, which enhances robustness and reduces variance across runs.

Ensemble methods (Dietterich, 2000) combine the outputs of multiple learners to improve stability and generalizability. Ensembles can be created through bagging (training models on different data subsets), boosting (sequentially correcting errors), or stacking (integrating structurally different models) (Sapp, van der Laan, & Canny, 2014). In our study, we first applied bagging to stabilize MLP predictions by aggregating outputs from multiple independently trained networks (Adeodato, Arnaud, Vasconcelos, Cunha, & Monteiro, 2011). Subsequently, we combined ensemble methods with XGBoost, allowing sequential correction of previous model errors. Both approaches improved model stability and generalizability, especially when paired with RFE.

In particular, ensemble MLPs achieved higher classification performance and lower variability, demonstrating that combining networks trained with different seeds reduces overfitting and increases reliability. To identify the optimal ensemble size, we employed the F-Race algorithm (Yuan, Stützle, & Birattari, 2010), which indicated that an ensemble of three networks was optimal.

The results of the classification exercises are reported in Tables 4 and 5, which present the main statistics of various performance metrics over 30 different train/test partitions. The metrics used in the evaluation include:

- **Precision:** In binary classification, precision corresponds to the proportion of elements predicted as positive that are actually positive. For multi-class classification, it is extended by computing an average across classes, either macro (arithmetic mean of per-class values) or micro

(computed globally). In this study, we report the micro-average precision.

- **Recall (Sensitivity):** In binary classification, recall is the proportion of correctly predicted positive elements relative to the total number of true positives. For multi-class problems, it can also be averaged using macro or micro approaches. Here, we report the micro-average recall.
- **Accuracy:** This metric measures the overall correctness of the predictions and is calculated as the number of correct predictions divided by the total number of predictions. This definition applies to both binary and multi-class classification.
- **F1 Score:** The F1 score represents the harmonic mean of precision and recall in binary classification. For multi-class classification, it can be computed as a macro-average (mean of per-class F1 scores) or a micro-average (derived from the globally averaged precision and recall). In this study, we report the micro-average F1 score.

Table 4: Results of the prediction of revenue growth by using different algorithms over features detected by Recursive Features Elimination.

Model	Precision Avg	Recall Avg	Precision Stdev	Recall Stdev
XGBoost	0.99	0.97	0.01	0.02
KNN	0.72	0.57	0.05	0.09
SVM	0.85	0.84	0.06	0.07
MLP	0.89	0.87	0.04	0.04
Ensemble MLP	0.96	0.97	0.03	0.02

Table 4 shows the main statistics of precision and recall, computed over 30 different partitions of train/test sets. Table 5 shows the main statistics of Accuracy and F1 score computed over 30 different partitions of train/test sets.

Table 5: Results of the prediction of revenue growth by using different algorithms over features detected by Recursive Features Elimination.

Model	Accuracy (Min)	Accuracy (Max)	Accuracy (Average)	Accuracy (Stdev)	F1 Score (Min)	F1 Score (Max)	F1 Score (Average)	F1 Score (Stdev)
XGBoost	0.9319	1.0000	0.9924	0.0154	0.9288	1.0000	0.9835	0.0192
KNN	0.6326	0.8889	0.7299	0.0612	0.3403	0.8619	0.5741	0.1218
SVM	0.8248	0.9590	0.8453	0.0625	0.7028	0.9802	0.8202	0.0757
MLP	0.8168	0.9480	0.8794	0.0046	0.7620	0.9485	0.8727	0.0662
Ensemble MLP	0.8849	1.0000	0.9675	0.0356	0.8258	1.0000	0.9558	0.0421

By keeping in mind that all metrics range from 0 to 1 (higher is better) and that each metric evaluates different aspects of classification performance, the results do not present any contradictions. Overall, all methods exhibit generally positive behavior, with XGBoost achieving the best results. Simpler methods, such as MLP, also deliver satisfactory performance, and their predictive capabilities can be further enhanced when used within an ensemble framework. These outcomes provide a positive assessment of the classification exercise, supporting the conclusion that computational intelligence methods can effectively predict companies' economic performance using their collected business features as predictors.

5. Discussion

The empirical analysis of Apulian tourism firms' business model configurations reveals a complex, dynamic, and often paradoxical relationship between business practices and revenue growth. As illustrated in Table 3, performance in this regional tourism system is shaped not merely by the adoption of innovation or accumulation of resources, but by the extent to which these resources and practices are strategically aligned with market demands and internal capabilities. Growth dynamics emerge from the interplay of enabling and inhibiting factors, highlighting the critical role of coherent business model integration. Enabling factors cluster around three mutually reinforcing domains. First, relational resources and external collaboration proved essential. Firms that actively cultivated relationships with suppliers, developed partnerships within their sector (2018), and engaged in cross-sector collaborations (2015) consistently

achieved stronger revenue growth. Such networks function as conduits for knowledge sharing, joint marketing, and co-creation of services, generating synergies that exceed the capabilities of individual firms and fostering innovation in a competitive market.

Second, financial readiness was a key enabler. Firms reporting easier access to financial resources for new investments (2015 and 2018) demonstrated higher growth potential, confirming that capital availability underpins the ability to scale operations and implement innovative strategies. Financial resources thus act as a necessary foundation for translating strategic intent into measurable performance outcomes.

Third, strategic adaptiveness emerged as a decisive behavioral driver. Firms that interpreted declining results as a stimulus for innovation and those that prioritized accessibility to potential customers displayed superior performance. This mindset reflects proactive market positioning, where challenges are transformed into opportunities for differentiation. Positive growth trajectories—evidenced by increases in average revenue, seasonal employment, and the share of domestic customers—reinforce the notion that aligning internal capabilities with market demand sustains long-term performance. The presence of conference facilities further underscores the benefits of product diversification, allowing firms to capture higher-value segments such as business tourism and reduce seasonality risks.

In contrast, several negative drivers highlight structural weaknesses and strategic misalignments. A prominent theme is technological misalignment. Firms that emphasized the technological content of services, customer acquisition processes, or CRM systems (2015 and, to a lesser extent, 2018) were associated with lower revenue growth. Similarly, investments in digital infrastructure or process digitalization, when pursued in isolation, correlated with weaker performance. These findings indicate that technology adoption alone may become a cost center rather than a source of competitive advantage if it is not strategically embedded in a coherent, market-oriented business model. Technology generates value only when it enhances customer engagement, supports collaborative networks, or aligns with strategic objectives.

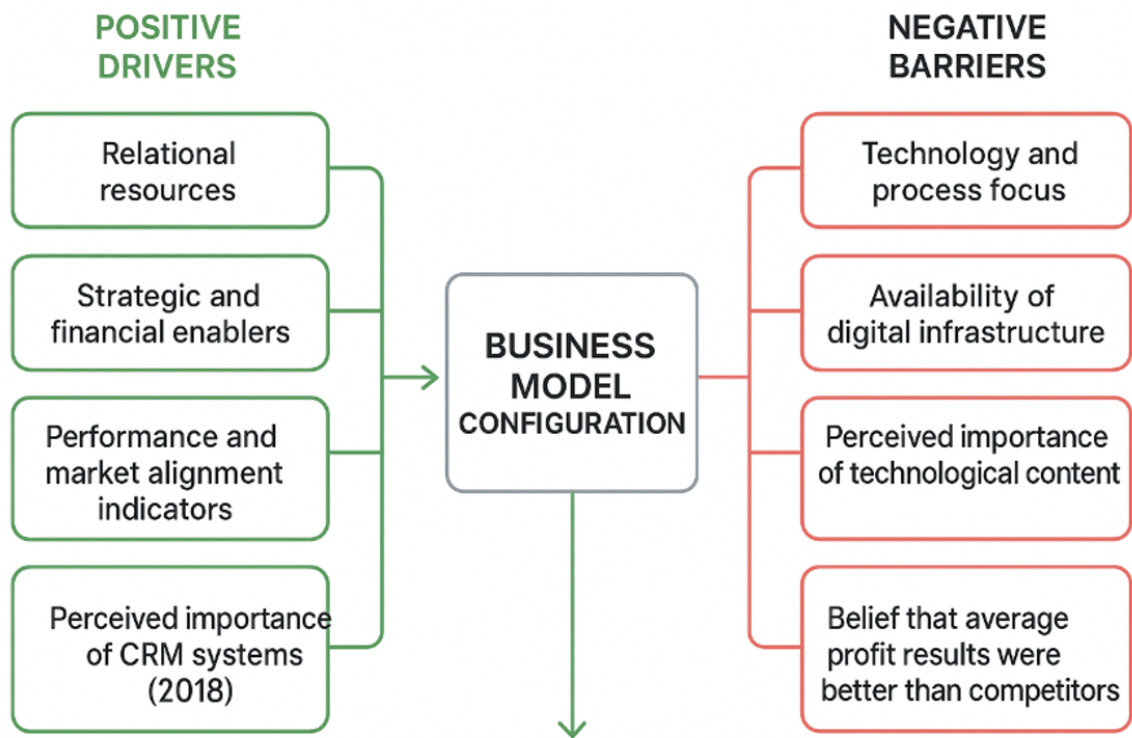
Strategic complacency and reactive innovation also acted as barriers. Firms that considered their 2015 profits superior to competitors or that viewed customer demands as the primary driver of innovation exhibited lower subsequent growth. Overconfidence in past performance fosters inertia, while reactive innovation—driven by external pressures rather than a forward-looking vision—fails to produce sustainable competitive advantages. This contrasts sharply with firms that treat declining results as a call to action: the former risk stagnation, while the latter leverage challenges as catalysts for transformation.

Taken together, these findings reveal a dual configuration of growth trajectories. Successful firms integrate external collaboration, financial readiness, and

proactive strategic adaptation, selectively leveraging customer-oriented digital tools to convert resources into tangible revenue growth. Underperforming firms, by contrast, either invest in technology without embedding it in a market-driven strategy or rely on past successes as proof of ongoing competitiveness, failing to capitalize on renewal opportunities. This duality underscores that growth is not simply a matter of “what” resources are acquired, but “how” they are orchestrated within the business model.

Figure 3 synthesizes these dynamics into a conceptual framework that links enabling and inhibiting factors, highlighting the central role of strategic alignment. It demonstrates that relational, financial, and innovation inputs drive growth only when integrated coherently, while misaligned technology investments or complacency can moderate or even reverse their benefits. Consequently, future competitiveness in Apulian tourism will depend less on the mere diffusion of digital infrastructure or incremental process upgrades and more on the development of capabilities to integrate resources into a forward-looking, outward-oriented, and market-aligned business model. This supports sustainability because it shows that tourism growth in Apulia is not just about adding more resources, but about aligning them strategically so they reinforce each other. When relational (partnerships, networks), financial, and innovation resources are coherently integrated, they generate long-term value, strengthen resilience, and reduce wasted investments. In contrast, misaligned efforts can drain resources, create inefficiencies, and undermine competitiveness—making growth unsustainable. By ensuring alignment, firms and policymakers can promote steady, balanced development that benefits businesses, communities, and the environment.

Figure 3.



Economic Performance and Sustainable Development Pathways in Firms

Source: authors' processing (2024)

The evidence emphasizes a shift from an inward-looking, technology-centered approach to an outward-facing, strategically coherent model. Firms that cultivate partnerships, maintain financial readiness, and adopt a proactive, adaptive mindset—using technology as a purposeful tool rather than an end in itself—are best positioned to transform inputs into sustained revenue growth. Firms that use technology as an enabler—embedded within a broader framework of social, financial, and environmental responsibility—are best positioned not only to transform inputs into sustained revenue growth but also to contribute to the long-term sustainability and resilience of the regional tourism ecosystem.

6. Conclusions

This study provides empirical evidence on the complex and dynamic relationship between business model (BM) configurations and revenue growth in the Apulian tourism sector. The findings highlight that performance is not solely driven by the accumulation of resources or the adoption of innovative practices

but critically depends on their strategic alignment with both market demands and internal firm capabilities. Firms that integrate relational networks, financial readiness, and proactive adaptive strategies within a coherent business model consistently achieve superior revenue growth, while misaligned technological investments or strategic complacency can undermine performance.

From a practical standpoint, these results highlight a shift from inward-focused, technology-centered approaches toward outward-oriented, market-aligned business models. In this view, technology functions as a facilitator rather than a primary driver of growth, creating value when it is strategically embedded to enhance customer engagement, strengthen collaborative networks, and complement the firm's core value proposition. Accordingly, firms should prioritize the coordination and orchestration of resources over the mere accumulation or sophistication of assets. Crucially, this perspective resonates with the principles of sustainability: long-term competitiveness is not achieved through resource intensification, but through the efficient mobilization of assets in ways that build relationships, foster innovation, and enhance the resilience of firms and their wider ecosystems. Sustainable growth in tourism thus emerges from business models that integrate technological advancement with social, financial, and environmental responsibility.

The application of both computational and traditional quantitative methods in this study demonstrates that predictive modeling can effectively anticipate the economic performance of tourism firms, provided that careful data preprocessing is applied. Several key insights emerge from the computational tools employed. First, rigorous data preprocessing is essential before applying any algorithm. Second, traditional methods can still achieve strong results when paired with thoughtful preprocessing, which is particularly relevant given their ease of implementation; users must balance the simplicity of these approaches against the higher costs of deploying more complex alternatives. Finally, computational intelligence tools should be considered complementary, as evidenced by the superior performance of Ensemble Methods over their individual base predictors. Collectively, these results indicate that the algorithms presented are well-suited for predicting the economic performance of tourism companies.

Despite its contributions, this research has limitations. The study focuses primarily on turnover as the measure of performance, which may not capture broader dimensions of firm success, such as customer satisfaction, brand reputation, or environmental sustainability. Future research should expand the set of performance indicators to include sustainability metrics—such as the adoption of certifications, the creation of sustainable stakeholder relationships, or ecological and social impacts beyond the firm's boundaries. Additionally, the generalizability of findings may be constrained by the regional focus on Apulian tourism firms; applying similar analyses to other regions or sectors would help validate

the observed patterns of strategic alignment and BM effectiveness. Finally, while computational intelligence methods showed promise, further refinement and testing with larger and more diverse sets of data could enhance their predictive reliability and operational applicability.

This study contributes both theoretically and methodologically by demonstrating the centrality of strategic alignment in business model performance and by providing a framework for combining traditional and data-driven approaches to predict firm outcomes. The results offer actionable insights for managers, policymakers, and financial decision-makers aiming to foster sustainable growth in tourism and related sectors.

References

- Abrahamsson, J., Boter, H., & Vanyushyn, V. (2019). Business model innovation of international new ventures: An empirical study in a Swedish context. *Journal of International Entrepreneurship*, 17(1), 75-102.
- Adeodato, P.J.L., Arnaud, A.L., Vasconcelos, G.C., Cunha, R.C.L.V. & Monteiro, D.S.M.P. (2011). "MLP ensembles improve long-term prediction accuracy over single networks", *International Journal of Forecasting*, Vol. 27 No. 3, pp. 661-671.
- Amit, R. & Zott, C. (2010). Business model innovation: creating value in times of change. *IESE Business School, Working Paper WP-870*.
- Amit, R., & Zott, C. (2020). Business model innovation strategy: Transformational concepts and tools for entrepreneurial leaders. New York.
- Amit, R., & Zott, C. (2012). Creating value through business model innovation. *MIT Sloan management review*, 53(3), 41.
- Andries, P., & Debackere, K. (2007). Adaptation and performance in new businesses: Understanding the moderating effects of independence and industry. *Small business economics*, 29(1), 81-99.
- Aversa, P., Furnari, S., & Haefliger, S. (2015). Business model configurations and performance: A qualitative comparative analysis in Formula One racing, 2005–2013. *Industrial and Corporate Change*, 24(3), 655–676.
- Baden-Fuller, C. & Haefliger, S. (2013) Business models and technological innovation. *Long Range Planning*, 46,6, 419–426.
- Baden-Fuller, C., & Mangematin, V. (2013) Business models: A challenging agenda, *Strategic Organization*, 11 (4), pp. 418-427.
- Bernini, C., & Galli, F. (2023). Innovation, productivity and spillover effects in the Italian accommodation industry. *Economic Modelling*, 119, 106145.

- Bigelow, L. S., & Barney, J. B. (2021). What can strategy learn from the business model approach? *Journal of Management Studies*, 58(2), 528–539.
- Bilgili, T. V., Calderon, C. J., Allen, D. G., & Kedia, B. L. (2017). Gone with the wind: A meta-analytic review of executive turnover, its antecedents, and postacquisition performance. *Journal of Management*, 43(6), 1966–1997.
- Bivona, E. & Cruz, M. (2021). Can business model innovation help SMEs in the food and beverage industry to respond to crises? Findings from a Swiss brewery during COVID-19, *British Food Journal*, 123 (11), pp. 3638–3660.
- Breier, M., Kallmuenzer, A., Clauss, T., Gast, J., Kraus, S., & Tiberius, V. (2021). The role of business model innovation in the hospitality industry during the COVID-19 crisis. *International journal of hospitality management*, 92, 102723.
- Brzezinski, D. (2020), "Fibonacci and k-subsecting recursive feature elimination", arXiv preprint, arXiv:2007.14920.
- Camatti, N., di Tollo, G., Filograsso, G., & Ghilardi, S. (2024). Predicting Airbnb pricing: a comparative analysis of artificial intelligence and traditional approaches. *Computational Management Science*, 21(1), 30.
- Camisón, C., & Monfort-Mir, V. M. (2012). Measuring innovation in tourism from the Schumpeterian and the dynamic-capabilities perspectives. *Tourism management*, 33(4), 776–789.
- Casadesus-Masanell, R. & Zhu, F. (2013). Business model innovation and competitive imitation: the case of sponsor-based business models. *Strategic Management Journal*, 34, 464–482. doi: 10.1002/smj.2022.
- Chen, T. & Guestrin, C. (2016). "XGBoost: A scalable tree boosting system", in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, ACM, pp. 785–794.
- Cavalcante, S., Kesting, P., & Ulhøi, J. (2011). Business model dynamics and innovation:(re) establishing the missing linkages. *Management decision*, 49(8), 1327–1342.
- Chesbrough, H (2010) Business model innovation: Opportunities and barriers. *Long Range Planning*, 43 (2–3), pp. 354–363, [10.1016/j.lrp.2009.07.010](https://doi.org/10.1016/j.lrp.2009.07.010)
- Chesbrough, H., & Rosenbloom, R. S. (2002). The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies. *Industrial and corporate change*, 11(3), 529–555.
- Clancey, W.J. (1984). *Classification Problem Solving*, Stanford University, Stanford, CA.
- Clausen, T. H., & Molden, L. H. (2024). Managerial ties, external resources, and business model innovation: Interplay and mediation analysis. *Journal of Small Business Management*, 62(6), 3164–3190.
- Clauss, T. (2017) Measuring business model innovation: Conceptualization, scale development, and proof of performance. *R&D Management*, 47 (3), pp. 385–403, [10.1111/radm.12186](https://doi.org/10.1111/radm.12186)

- Clauss, T., Abebe, M., Tangpong, C., & Hock, M. (2019). Strategic agility, business model innovation, and firm performance: an empirical investigation. *IEEE transactions on engineering management*, 68(3), 767-784.
- Confente, I., Mazzoli, V., Camatti, N., & Bertocchi, D. (2024). Integrating tourists' walk and talk: a methodological approach for tracking and analysing tourists' real behaviours for more sustainable destinations. *Journal of Sustainable Tourism*, 32(11), 2323-2343.
<https://doi.org/10.1080/09669582.2024.2322120>
- Corazza, M., De March, D., & Di Tollo, G. (2021). Design of adaptive Elman networks for credit risk assessment. *Quantitative Finance*, 21(2), 323-340.
- Cortes, C. and Vapnik, V. (1995). "Support-vector networks", *Machine Learning*, Vol. 20 No. 3, pp. 273-297.
- Cosenz, F., & Bivona, E. (2021). Fostering growth patterns of SMEs through business model innovation. A tailored dynamic business modelling approach. *Journal of Business Research*, 130, 658-669.
- Cucculelli, M., & Bettinelli, C. (2015). Business models, intangibles and firm performance: evidence on corporate entrepreneurship from Italian manufacturing SMEs. *Small Business Economics*, 45(2), 329-350.
- Cucculelli, M., & Peruzzi, V. (2020). Post-crisis firm survival, business model changes, and learning: Evidence from the Italian manufacturing industry. *Small Business Economics*, 54, 459-474.
- Demil, B., & Lecocq, X. (2010). Business model evolution: In search of dynamic consistency. *Long range planning*, 43(2-3), 227-246.
- Dietterich, T.G. (2000), "Ensemble methods in machine learning", in *Proceedings of the International Workshop on Multiple Classifier Systems*, Springer, pp. 1-15.
- D'Ippolito, B., Messeni A., Petruzzelli, & U. Panniello (2019). Archetypes of incumbents' strategic responses to digital innovation *Journal of Intellectual Capital*, 20 (5), pp. 662-679, [10.1108/JIC-04-2019-0065](https://doi.org/10.1108/JIC-04-2019-0065)
- di Tollo, G., Andria, J., Tanev, S. & Ghilardi, S. (2024). Integrating the gender dimension to disclose the degree of businesses' articulation of innovation. *J Comput Soc Sc* 7, 87-123. <https://doi.org/10.1007/s42001-023-00230-x>
- França, C.L., Broman, G., Robèrt, G. H., & Basile, L. (2017). An approach to business model innovation and design for strategic sustainable development *Journal of Cleaner Production*, 140, pp. 155-166, [10.1016/j.jclepro.2016.06.124](https://doi.org/10.1016/j.jclepro.2016.06.124)
- Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: how far have we come, and where should we go? *Journal of management*, 43(1), 200-227.
- Galton, F. (1886). "Regression towards mediocrity in hereditary stature", *The Journal of the Anthropological Institute of Great Britain and Ireland*, Vol. 15, pp. 246-263.

- George, G., & Bock, A. J. (2011). The business model in practice and its implications for entrepreneurship research. *Entrepreneurship Theory and Practice*, 35(1), 83–111.
- Guo, G., Wang, H., Bell, D., Bi, Y., & Greer, K. (2003). KNN Model-Based Approach in Classification. In: Meersman, R., Tari, Z., Schmidt, D.C. (eds) On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE. OTM 2003. *Lecture Notes in Computer Science*, vol 2888. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-39964-3_62
- Guyon, I., Weston, J., Barnhill, S. & Vapnik, V. (2002). "Gene selection for cancer classification using support vector machines", *Machine Learning*, Vol. 46, pp. 389-422.
- Hjalager, A. M. (2010). A review of innovation research in tourism. *Tourism management*, 31(1), 1-12.
- Johnson, M. W., Christensen, C. M., & Kagermann, H. (2008). Reinventing your business model. *Harvard business review*, 86(12), 50-59.
- Kamasak R., Yavuz M., Karagulle A. O., & Agca T. (2016). Importance of strategic flexibility on the knowledge and innovation relationship: An emerging market study. *Procedia - Social and Behavioral Sciences*, 229, 126–132. <https://doi.org/10.1016/j.sbspro.2016.07.121>
- Kiefer, J. & Wolfowitz, J. (1959). "Optimum designs in regression problems", *Annals of Mathematical Statistics*, Vol. 30 No. 2, pp. 271-294.
- Kim, W. C., & Mauborgne, R. (2014). How to Develop and Select Your New Leadership Profiles. *Blue Ocean Leadership Series IV*.
- Kindström, D., Carlborg, P., & Nord, T. (2024). Challenges for growing SMEs: A managerial perspective. *Journal of small business management*, 62(2), 700-723.
- Kraus, S., Filser, M., Puumalainen, K., Kailer, N., & Thurner, S. (2020). Business model innovation: A systematic literature review. *International Journal of Innovation and Technology Management*, 17(6), 2050043.
- Lanzolla, G. & Markides, C. (2021) A business model view of strategy. *Journal Management Studies*, 58, pp. 540-553
- Latifi, M. A., Nikou, S., & Bouwman, H. (2021). Business model innovation and firm performance: Exploring causal mechanisms in SMEs. *Technovation*, 107, 102274.
- Magretta, J. (2002). 'Why Business Models Matter?' *Harvard Business Review*. 80 (5): 3–8.
- Martínez-Román, J. A., Tamayo, J. A., Gamero, J., & Romero, J. E. (2015). Innovativeness and business performances in tourism SMEs. *Annals of Tourism Research*, 54, 118-135.
- Markides, C., & Charitou, C.D (2004). Competing with dual business models: A contingency approach. *Academy of Management Perspectives*, 18 (3) pp. 22-36, [10.5465/ame.2004.14776164](https://doi.org/10.5465/ame.2004.14776164)

- Massa, L., & Tucci, C.L. (2013). Business model innovation M. Dodgson, D.M. Gann, N. Phillips (Eds.), *The Oxford Handbook of Innovation Management*, OUP Oxford, pp. 420-441
- Massa, L., Tucci, C., & Afuah, A. (2017). A critical assessment of business model research. *Academy of Management Annals*, 11, 73–104.
- McGrath, R.G. (2010). Business models: A discovery driven approach, *Long Range Planning*, 43, pp. 247-261.
- Miller, D. (1996). Configurations revisited. *Strategic management journal*, 17(7), 505-512.
- Morris, M., M. Schindehutte, & J. Allen. (2005). 'The Entrepreneur's Business Model: Toward a Unified Perspective.' *Journal of Business Research*. 58 (6): 726–35.
- Naseriparsa, M., Bidgoli, A-M. & Varae, T. (2014). "A hybrid feature selection method to improve performance of a group of classification algorithms", arXiv preprint, arXiv:1403.2372.
- Osservatorio Turistico (2024) <https://www.regione.puglia.it/web/ufficio-statistico>
- Osterwalder, A., Pigneur, Y. & Tucci, C. L. (2005). 'Clarifying Business Models: Origins, Present, and Future of the Concept.' *Communications of the Association for Information Systems*. 16:1–25.
- Osterwalder, A., & Pigneur, Y. (2010) *Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers*. John Wiley & Sons
- Pardeshi, N.G. & Patil, D.V. (2023). "Applying gini importance and RFE methods for feature selection in shallow learning models for implementing effective intrusion detection system", in *Proceedings of the International Conference on Applications of Machine Intelligence and Data Analytics (ICAMIDA 2022)*, Atlantis Press, pp. 214-234.
- Presenza, A., Messeni Petruzzelli, A., & Natalicchio, A. (2019). Business model innovation for sustainability. Highlights from the tourism and hospitality industry. *Sustainability*, 11(1), 212.
- Rauch, A., Wiklund, J., Lumpkin, G. T., & Frese, M. (2009). Entrepreneurial orientation and business performance: An assessment of past research and suggestions for the future. *Entrepreneurship theory and practice*, 33(3), 761-787.
- Rauter R., Jonker J., & Baumgartner R. J. (2017). Going one's own way: Drivers in developing business models for sustainability. *Journal of Cleaner Production*, 140, 144-154.
- Reinhold, S., Beritelli, P., & Grünig, R. (2019). A business model typology for destination management organizations. *Tourism Review*, 74(6), 1135-1152.
- Reuver, M., Bouwman, H., & Haaker, T. (2013). Business Model Roadmapping: A Practical Approach to Come from an Existing to a Desired Business Model. *International Journal of Innovation Management*, 17 (01), p. 1340006, [10.1142/S1363919613400069](https://doi.org/10.1142/S1363919613400069)

- Rosenblatt, F. (1958). "The perceptron: A probabilistic model for information storage and organization in the brain", *Psychological Review*, Vol. 65 No. 6, pp. 386-408.
- Rosenbusch, N., Rauch, A., & Bausch, A. (2013). The mediating role of entrepreneurial orientation in the task environment-performance relationship: A meta-analysis. *Journal of management*, 39(3), 633-659.
- Salfore, N., Ensermu, M., & Kinde, Z. (2023). Business model innovation and firm performance: Evidence from manufacturing SMEs. *Heliyon*, 9(6).
- Sapp, S., van der Laan, M.J. & Canny, J. (2014). "Subsemble: An ensemble method for combining subset-specific algorithm fits", *Journal of Applied Statistics*, Vol. 41 No. 6, pp. 1247-1259.
- Shafer, S.M., Smith, H. J., & Linder, J. C. (2005). The power of business models, *Business horizons*, 48(3), 199-207
- Sirmon, D.G., Hitt, M.A. & Ireland, R.D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of Management Review*, 32, 273-292.
- Sirmon, D.G., Hitt, M.A, Ireland, R.D., & Gilbert, B.A. (2011). Resource Orchestration to Create Competitive Advantage: Breadth, Depth, and Life Cycle Effects, *Journal of Management*, 37 (5), pp. 1390-1412, [10.1177/0149206310385695](https://doi.org/10.1177/0149206310385695)
- Sørensen, J. B. (2002). The strength of corporate culture and the reliability of firm performance. *Administrative science quarterly*, 47(1), 70-91.
- Spieth, P., & Schneider, S. (2016) Business model innovativeness: designing a formative measure for business model innovation. *J Bus Econ*. 86, 671-696
- Spieth, P. & Schneckenberg, D.J.E. (2014) Ricart Business model innovation - state of the art and future challenges for the field. *R&D Management*, 44 (3), pp. 237-247, [10.1111/radm.12071](https://doi.org/10.1111/radm.12071)
- Teece, D. J. (2010). Business models, business strategy and innovation. *Long range planning*, 43(2-3), 172-194.
- Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro-foundations of (sustainable) enterprise performance. *Strategic management journal*, 28(13), 1319-1350.
- Urbinati, A., Manelli, L., Frattini, F., & Bogers, M. L. (2022). The digital transformation of the innovation process: Orchestration mechanisms and future research directions. *Innovation*, 24(1), 65-85.
- Visnjic, I., Wiengarten, F., & Neely, A. (2016). Only the brave: Product innovation, service business model innovation, and their impact on performance. *Journal of product innovation management*, 33(1), 36-52.
- Voelpel, S.C., Leibold, M., & Tekie, E.B. (2004). The wheel of business model reinvention: How to reshape your business model to leapfrog competitors, *Journal of Change Management*, 4 (3), pp. 259-276, [10.1080/1469701042000212669](https://doi.org/10.1080/1469701042000212669)

- Voelpel, S. C., M. Leibold, E. B. Tekie, & G. von Krogh. (2005). 'Escaping the Red Queen Effect in Competitive Strategy: Sense-Testing Business Models.' *European Management Journal*, 23 (1): 37-49.
- Wiggins, R. R., & Ruefli, T. W. (2002). Sustained competitive advantage: Temporal dynamics and the incidence and persistence of superior economic performance. *Organization science*, 13(1), 81-105.
- Wirtz, B. W., A. Pistoia, S. Ullrich, & V. Göttel. (2016). 'Business Models: Origin, Development and Future Research Perspectives.' *Long Range Planning* 49 (1): 36-54.
- Wirtz, B.W. & Daiser, P. (2018). Business Model Innovation Processes: A Systematic Literature Review. *Journal of Business Models*, 6 (1), pp. 40-58, [10.5278/OJS.JBM.V6I1.2397](https://doi.org/10.5278/OJS.JBM.V6I1.2397)
- Xia, S. & Yang, Y. (2023). "A model-free feature selection technique of feature screening and random forest-based recursive feature elimination", *International Journal of Intelligent Systems*, Vol. 2023 No. 1, p. 2400194.
- Yuan, Z., Stützle, T. & Birattari, M. (2010). "MADS/F-Race: Mesh adaptive direct search meets F-Race", in García-Pedrajas, N., Francisco, H., Fyfe, C., Benítez, J.M. & Ali, M. (2010). (Eds), *Trends in Applied Intelligent Systems, 23rd International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems (IEA/AIE 2010)*, Lecture Notes in Artificial Intelligence, Vol. 6096, Springer, Berlin, pp. 41-50. (Conference held in Córdoba, Spain, June 1-4, 2010).
- Zhang-Zhang, Y., Rohlfer, S., & Varma, A. (2022). Strategic people management in contemporary highly dynamic VUCA contexts: A knowledge worker perspective. *Journal of Business Research*, 144, 587-598.
- Zott, C., & Amit, R. (2007). Business model design and the performance of entrepreneurial firms. *Organization Science*, 18(2), 181-199.
- Zott, C., & Amit, R. (2013). The business model: A theoretically anchored robust construct for strategic analysis. *Strategic Organization*, 11(4), 403-411
- Zott, C., Amit, R., & Massa, L. (2011). The business model: Recent developments and future research. *Journal of Management*, 37(4), 1019-1042.