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Contents

PECULIARITIES OF DESIGN THINKING IMPLEMENTATION ON ROMANIAN COURIER INDUSTRY FROM A DYNAMIC MANAGERIAL CAPABIITY 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.

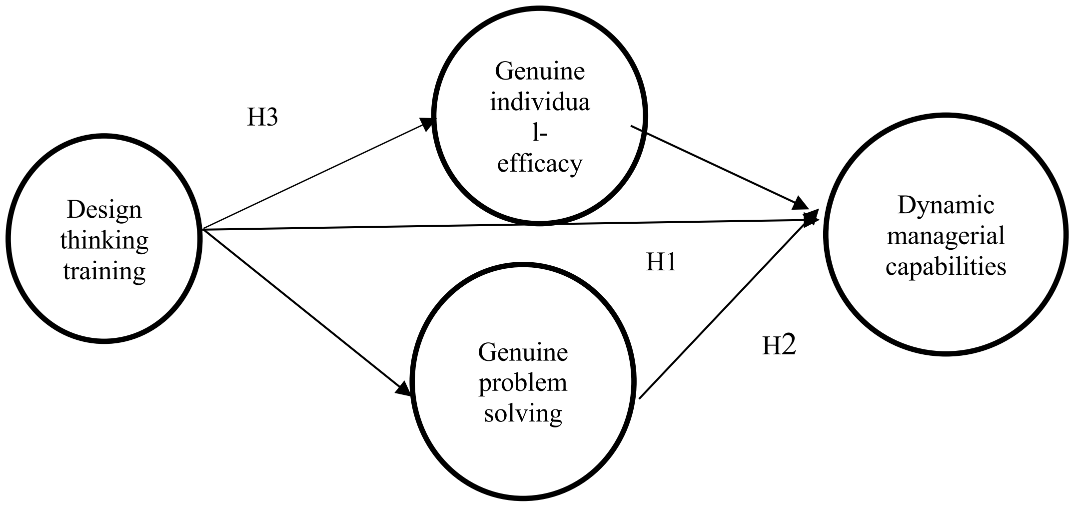

Figure 1. Theoretical research model.

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

	Intervention group		Control group		*F* test	*p*
Variable	M	SD	M	SD		value
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

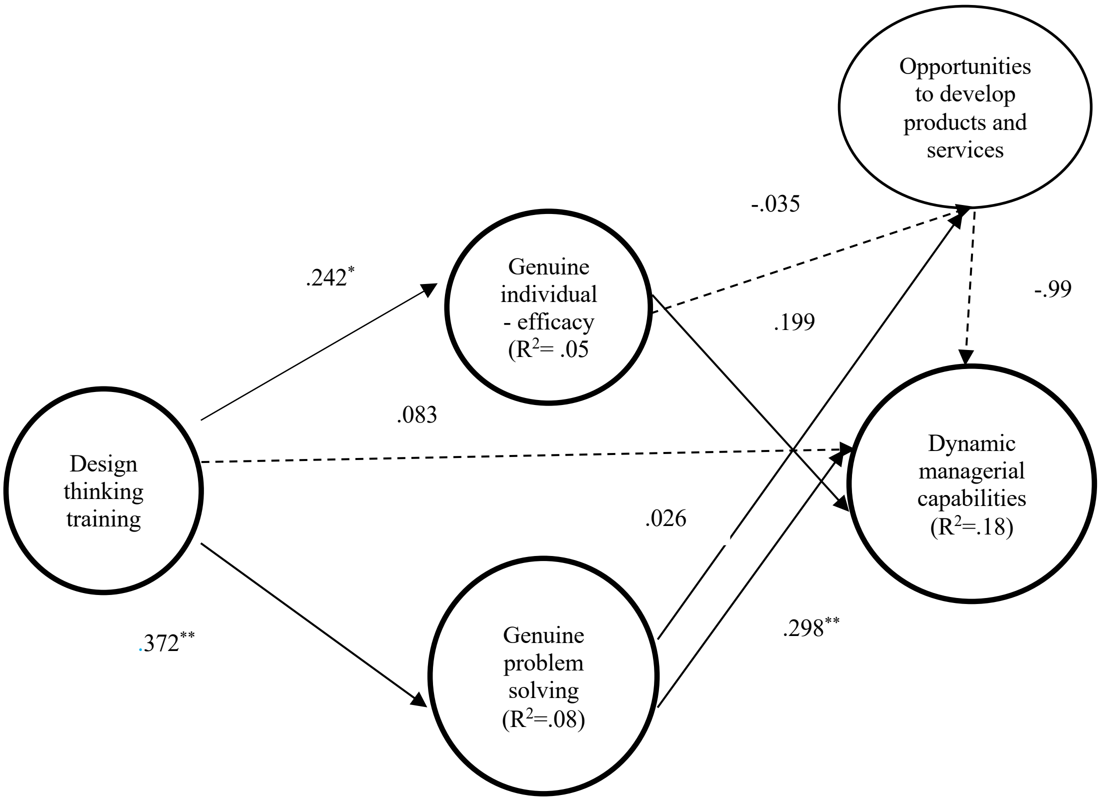

Figure 2. Model path and significant path coefficients, without controls.

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.

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TOURISM SUSTAINABLE DEVELOPMENT THROUGH BUSINESS MODEL RECONFIGURATION: 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 complimentary 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.

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

Paper type Original Paper

Introduction

The contemporary business environment in the digital era is characterized by high volatility and rapid changes in the way businesses compete, reflected in considerable ambiguity and significant uncertainty (Zhang-Zhang et al., 2022). These ever-changing dynamics of the external environment impact firm behaviour in the way they quickly react and adapt to the new market changes by implementing innovations in 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 and Schneider, 2016; Clauss, 2017), becoming the source of success and firm competitive advantage (Zott and Amit, 2007).

For management researchers, BM is a conceptual tool reflected by the business's core value proposition(s) for customers, in which the relevant activities of a company are represented in an aggregated and simplified way (Wirtz et al., 2016), which itself 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, and research recognize the high risk that accompanies innovation of a companies' BM in guaranteeing success after substantial changes (Kindström et al., 2024), failing to ensure long-term survival (Casadesus-Masanell and 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 and Lecocq, 2010). The reasons for failure should be sought in managers' lack of understanding of their organizations' business models, their unique building blocks, and the potential they have for creating a distinct competitive advantage (Zott and Amit, 2007).

In this study, we aim to complement previous research on the vagueness of the results regarding the relationship between BMI and firm performance. Unlike the previous studies, which examine the average firm performance (Cucculelli and Bettinelli, 2015; Salfore et al., 2023), we address Sorensen's call (2002) to understand the effectiveness of the new business model components in firm performance and the type of association that exists between BMI and firm performance (positive or negative). This reflects on sustainability 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 considers 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 specificity of the tourism sector, this study aims to broaden our understanding of how the representation of a firm's underlying core logic and strategic choices for creating sustainable competitive advantage (Morris, Schindehutte, and Allen 2005) and for making and capturing value within a value network (Shafer et al., 2005; Teece, 2010), converting that value to profit.

Innovation of companies' BMs represents both an important managerial task and a crucial capability of entrepreneurial ventures (Cosenz and Bivona, 2021; Clausen and Molden, 2024) that ensures companies' alignment with the new business conditions and current emerging market competitive actions (Teece, 2007) that reorganize themselves to best meet customers' needs. This necessary "evolution fit" of the way companies innovate their operations encompasses a considerable body of research in which scholarly work has delved into unveiling the favorable outcomes of the relationship between business model innovation (BMI) and performance.

In the literature, numerous studies highlight the vagueness surrounding the relationship between BMI and company performance, which is a complex phenomenon that depends on various contingency factors. Every firm employs a specific business model in pursuit of a competitive advantage. However, this pursuit is complicated and sometimes unsuccessful. Idiosyncratic examples from company-specific reconfiguration of building blocks of business models 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 the competitiveness of Apulian tourism relies largely on the strategic alignment of resources: relational, financial and responsible development are mutually achievable goals.

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 experimental 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 experiments 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 2.2, 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 data analysis and discussion, respectively.

Business models

In contemporary management literature, the business model has been linked to the emerging 'knowledge economy' and the expansion of e-commerce (Teece, 2010: 174). Business models were popular in the early 1990s as a means for small enterprises to successfully compete with larger corporations on a worldwide basis. Their conceptualization as configurations of several components (Baden-Fuller and Mangematin, 2013; Morris et al., 2005) that make it easier to manage the factors that influence company performance (Bigelow and Barney, 2020; Lanzolla and Markides, 2021) is the foundation of the concept's practical and scholarly appeal. In this line of conceptualization, among the many frameworks that have been presented, Osterwalder and Pigneur's (2010) BM framework—which consists of nine basic blocks—is the most popular and comprehensive. According to authors, the fundamental element is a value proposition; the elements required for value creation are partnerships, activities, resources, and cost structures; and the methods by which value is delivered and some of it may be captured are defined by customer segments, customer relationships, distribution channels, and revenue streams.
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). Nevertheless, previous research agrees that business models are a set of interconnected design components that show a company's architecture for converting an entrepreneurial opportunity into a successful business (Aversa et al., 2015; Baden-Fuller & Mangematin, 2013; Bock et al., 2021). As a result, an established business model illustrates how resources and capabilities are organized both inside and outside of firm boundaries, which stakeholders use which of the resources and capabilities, how they do so, and why the end-to-end architecture works reliably (Amit and Zott, 2020).
Therefore, specific BM characteristics influence a company's performance (Zott & Amit, 2007) and superior performance is linked to business models that are more innovative and effective in organizing, combining, and utilizing resources and talents in the marketplace (Simon et al., 2011; Zott and Amit (2007). According to Simon et al. (2007) and Zott (2003), the dynamic process of

resource management inside a particular business model explains 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 because this competitive advantage may eventually fade (Sirmon et al., 2010; Wiggins and Ruefli, 2002), and innovation assets drive growth only when they are coherently and synergistically integrated. 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 resp

Business model innovation and firm performance

Business Model Innovation (BMI) is a key concept in entrepreneurship and strategic management. Innovating business models is crucial for both established companies and startups. External factors such as the current Covid-19 pandemic (Bivona and Cruz, 2021; Breier et al., 2021; Harms et al., 2021), increasing competition from new market entrants (D'Ippolito et al., 2019; Johnson et al., 2008), changing customer needs (Kim and Mauborgne, 2014; Zollenkop, 2009), the influence of new digital technologies (Jodlbauer and Strasser, 2016; Urbinati et al., 2022), and sustainability demands (França et al., 2017) all contribute to its growing importance. Developing products and services, creating new distribution channels, adopting new technologies, and forming new partnerships are all examples of business model innovation (Reuver et al., 2013). More than process or product/service innovation, BMI is essential for success (Amit & Zott, 2012; Johnson et al., 2008). Literature suggests that because the fundamental relationships between BM components can be unpredictable and difficult to change over time, the configurational nature of BMs makes BMI more challenging (Demil and Lecocq, 2010). Multiple components need to be altered for successful BMI, and the outcomes depend on how these components interact with each other. This increases the unpredictability of BM innovation, making it difficult to predict in advance whether a certain BM will succeed (Andries and Debackere, 2007; Cavalcante et al., 2011; McGrath, 2010).

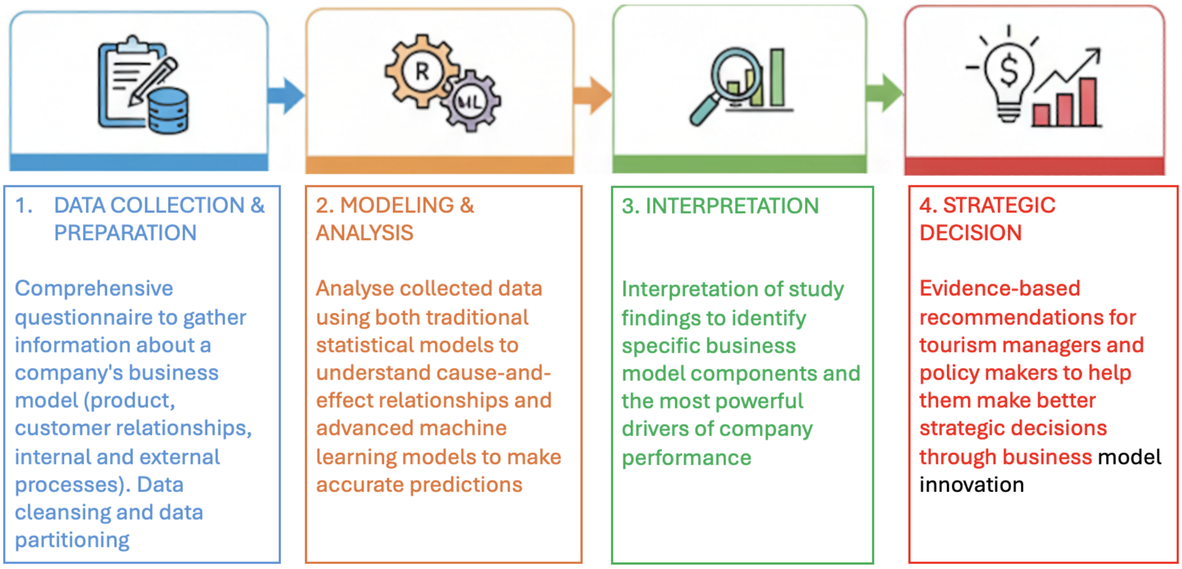
But both types of innovation are often combined, especially when businesses aim to become more competitive by providing better customer-focused products and services. Reconfiguring an existing business model is called business model innovation in established companies (Casadesus-Masanell and Zhu, 2013, Massa and Tucci, 2013). BMI is defined by Amit and Zott (2020) as a company's strategic approach to innovating the governance, content, structure, and value logic of the business model. From this perspective, BMI offers current businesses the "potential for enduring competitive advantage" when they reorganize their competencies and resources both within and outside the firm boundaries (Abrahamsson et al., 2019:77).

Regarding firm performance, meta-analyses often consider the lack of agreement in management literature about how to define and measure business performance (Rosenbusch et al., 2013). Prior research (e.g., Rauch et al., 2009; Bilgili et al., 2017) uses various measures for firm performance: sales-based metrics (such as sales growth, revenue from services, and revenue from new products), financial market indicators (like stock market returns and Tobin's Q), and self-reported subjective assessments. The common belief that BMI is essential to a company's performance (Zott et al., 2011) rests on a somewhat unclear and inconclusive empirical basis (Foss and Saebi, 2017; Hartmann et al., 2013; Latifi et al., 2021), and recent research has begun to question this view, suggesting BMI may negatively impact performance (Clauss et al., 2019; Visnjic et al., 2016). The complex "paths to monetization" linking innovation, company success, and the business model remain subject to debate (Baden-Fuller and Haefliger, 2013: 422).

2. Method

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, an analytical 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 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.

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.

2.1. Case Study: Application to the Apulia 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.
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.

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.

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					
	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		2.2.10					
	2.1.11	3.2.8	3.3.6		2.2.11					
			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. Experimental Design

This section presents the experimental 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, & Varaee, 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).

3.1. Experiments 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 are 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_201516	**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 features of a firm, can predict

Table 3: BM components predictive of revenue growth. (BE Component: blue = positive effect on revenue growth; gray = negative effect on revenue growth)

Question Number	
S1Q062	1.6 Trend of average revenue
S1Q063	1.6 Trend of the number of seasonal employees
S1Q072	1.7 Average number of seasonal employees in 2018
S1Q081	1.8 Percentage of turnover from Italian clients
S1Q09_b	1.9b Revenue class in 2018
S2Q01_a_201501	2.1 Importance of the technological content of the service offered in 2015
S2Q01_a_201801	2.1 Importance of the technological content of the service offered in 2018
S2Q01_a_201504	2.1 Importance of customer acquisition processes in 2015
S2Q01_a_201804	2.1 Importance of customer acquisition processes in 2018
S2Q01_a_201509	2.1 Importance of using Customer Relationship Management systems in 2015
S2Q01_a_201809	2.1 Importance of using Customer Relationship Management systems in 2018
S2Q01_b_201813	2.1 Importance of relationships with suppliers in 2018
S2Q01_b_201515	2.1 Importance of access to financial resources for new investments in 2015
S2Q01_b_201815	2.1 Importance of access to financial resources for new investments in 2018
S2Q01_b_201816	2.1 Importance of partnerships with other firms in the same sector in 2018
S2Q01_b_201517	2.1 Perceived importance of partnerships with firms in other sectors in 2015
S2Q02_06	2.2 Considers the deterioration of company results as a stimulus for innovation
S2Q02_07	2.2 Considers customer demands as a stimulus for innovation
S3Q01_20152	3.1 Believes that the average profit results in 2015 were better than those of competitors
S3Q02_05	3.2 Believes that accessibility (ability to become known to potential customers) has been a success factor for the company
S3Q02_08	3.2 Believes that the management of business processes has been a success factor for the company
S4Q023	4.2 Availability of technology and digital infrastructure (e.g., Wi-Fi, satellite services, management processes, software, etc.)
S4Q051	4.5 Investments made in the digitalisation of management processes
S5Q05_b22	5.5 Availability of conference facilities

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.

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). The same holds for S5Q05_b22 , showing that

2.1.2 Experiments 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.

1. **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
MPL	0.89	0.87	0.04	0.04
Ensemble MPL	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.

2. **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.

3 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.

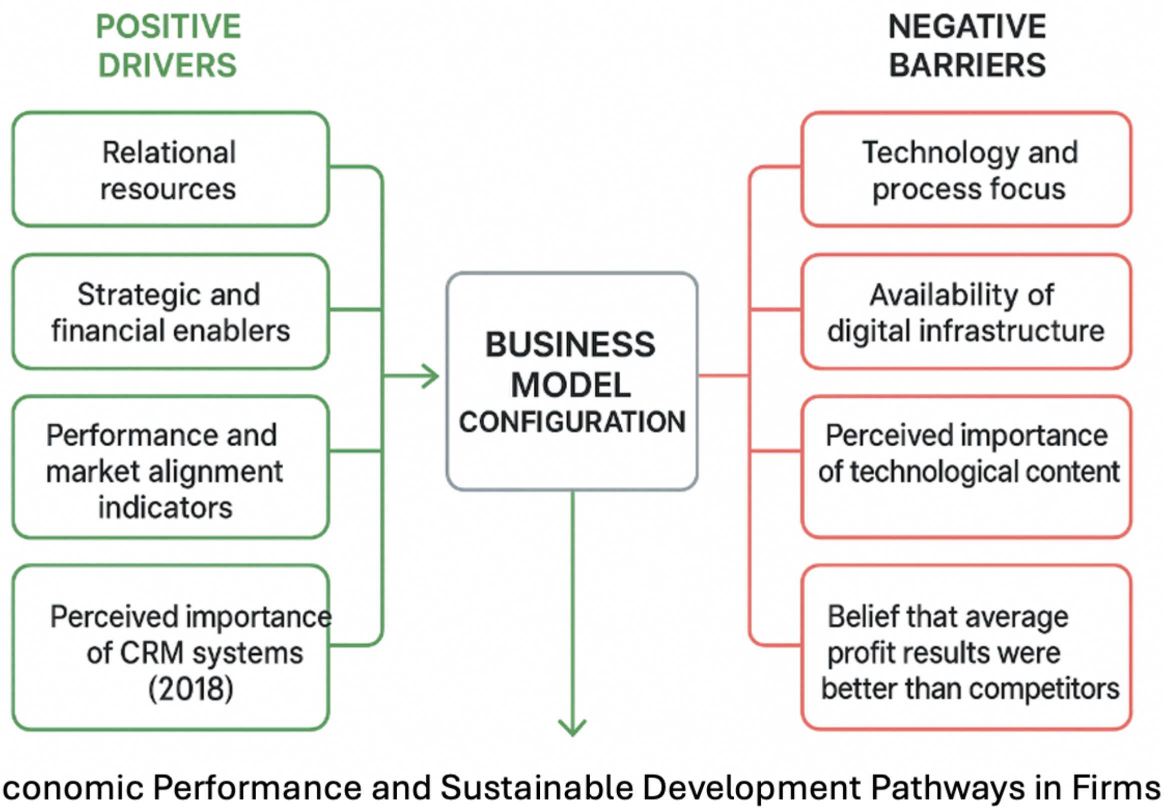
In contrast, several negative drivers highlight structural weaknesses and strategic misalignments. A prominent theme is technological misalignment. Firms that emphasized the technological content of services, customer acquisition processes, or CRM systems (2015 and, to a lesser extent, 2018) were associated 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.



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.

4. 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.

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INNOVATION IN DESIGN THINKING FROM A ROMANIAN ENTREPRENEURIAL PERSPECTIVE

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Abstract
This study explored the underlying mechanisms of empathy and motivation in innovation in design thinking from an entrepreneurial perspective. We built an explanatory model to examine the effect of empathy on motivation and innovation and the mediating effects of four aspects of motivation. In the study, 247 entrepreneurs participated in research centered on design thinking activities that lasted from November 2024 to September 2025, and then completed a questionnaire measuring their perceptions of empathy, motivation, and innovation at the end of the design activities. PLS SEM was used to analyze the collected data. The results showed that empathy positively predicted innovation. In addition, empathy had a significant impact on innovation through the effect of intrinsic motivation, but not through that of extrinsic motivation. Among the four aspects of motivation, attention, pertinence, and trust each strengthened the association between empathy and innovation. However, fulfillment had a negative effect on innovation and a non-significant mediating effect. These findings increase our understanding of the internal mechanisms of design thinking and innovation. Some practical implications of empathy and motivation in innovation are also discussed.
Keywords: Design thinking; Entrepreneurship; Innovation

1.Introduction

Innovation is regarded as an important skill in the 21st century (Ritter et al., 2014; Henriksen et al., 2016). It is generally considered to be the skill or ability to produce ideas or products that are novel and appropriate (Sternberg, 2001), rather than trivial or bizarre (Yaniv, 2012). As the essence of innovation is creative problem-solving (Casakin et al., 2021), problem-centered instruction has become the dominant tool for fostering entrepreneur' innovation (Livingston, 2010). And it has proved to be effective in promoting entrepreneur's innovation (Jeno et al., 2019). Design-based problems are a type of authentic problems that can foster innovation (Casakin et al., 2021).

Design thinking is a methodology for creatively solving design-based problems and developing innovation (Carlgren et al., 2016; Dorst, 2011). Its core idea is human-centered design (Brown, 2008), in which problems are identified and defined through empathizing and then solved by generating creative ideas or solutions (Razzouk et al., 2012).

Empathizing is the first step in design thinking and is a core element throughout the design process (Woo et al., 2018). Empathy is the complex cognitive and emotional state of taking on the perspective of another people and experiencing their emotions and thoughts, and it involves cognitive understanding (related to thought and ideas) and affective responses (related to emotions and feelings) (Kouprie et al., 2009). Empathy is considered to be a necessary qualification and ability in design because being empathetic is the key to discovering or defining the design problem or real needs and to inspiring innovation (Kouprie et al., 2009). Some studies have found that empathy contributes mainly to the usefulness or appropriateness aspect of innovation (Grant et al., 2011).

Other studies have found that motivation is also essential to innovation (Csikszentmihalyi, 1988). Motivation generally refers to "what people desire, what they choose to do, and what they commit to do" (Keller, 2010, p. 3). People who are more intrinsically motivated will have higher degrees of involvement, cognitive effort, and willingness to take risks, and less interference from external conditions when completing tasks, so their creative performance will be greater (Hennessey et al., 2010). It has been suggested that intrinsic motivation positively predicts innovation (Grant et al., 2011). Individuals who are more intrinsically motivated are more likely to persist with challenging and complex problem-solving tasks (Gagné et al., 2005). However, some research has found weak, mixed, or even no prediction by motivation for innovation, especially when the tasks involve providing service to others (Amabile et al., 2016; Grant et al., 2011). A possible interpretation of this phenomenon is that intrinsic motivation leads people to focus on the novelty aspect of innovation to pursue their interests and satisfying their curiosity (Grant et al., 2011). However, usefulness must also be considered in the generation of creative ideas (Grant et al., 2011).

Thus, individuals' empathy and motivation are two important factors that influence innovation, as creative design problem-solving involves not only rational or logical thinking but also non-rational dimensions of creative thinking such as empathy and motivation (Csikszentmihalyi, 1988). However, the relationship between these factors has rarely been investigated (Yaniv, 2012). The synergistic effect of empathy and motivation with innovation has also received little attention. Most previous studies have found direct of empathy and motivation on individuals' creativity, respectively (Lee et al., 2021; Woo et al., 2018). Empathy and motivation may work in synergy with innovation because novelty and usefulness are both indispensable components of creativity (Sternberg, 2001). Therefore, the current research explored the mechanisms underlying the relationships between empathy and motivation on individuals' innovation in design thinking.

2. Literature review and research hypotheses

2.1. Improving innovation through design thinking

Design thinking is not only a methodology for creatively solving design-based problems but also an approach to developing individuals' creativity (Brown, 2008; Carlgren et al., 2016; Dorst, 2011). Design activity is an indispensable part of design thinking because it is considered the core problem-solving process of technological development (Lewis, 2006). Design thinking has been considered an approach or methodology for solving problems (Lewis, 2006). In design-based problem-solving, design fields include software design (Kao et al., 2017) and product manufacturing (Kao et al., 2017), engineering design (Huang et al., 2020), architectural design (Casakin et al., 2021), and business management (Yannou, 2013). Research has indicated that design thinking is important for designers to solve real-world problems in creative and meaningful ways (Balakrishnan, 2022; Guaman-Quintanilla et al., 2023). For instance, Balakrishnan (2022) found that design thinking helped entrepreneurs' designers to become more creative, thus enabling them to develop practical and innovative designs. Both systematic reviews and meta-analyses have revealed that design thinking can be an effective method of promoting innovation (Micheli et al., 2019).

Previous research has mainly focused on logical problem-solving in innovation and rational thinking strategies in design thinking, such as analyzing and synthesizing (Csikszentmihalyi, 1988). However, in the solving of design problems, some logical or systematic thinking strategies such as lateral thinking may be inefficient because the design process is usually associated with a non-logical thinking method, i.e., the non-rational dimensions of creative thinking. These non-rational aspects of innovation, which include motivation and empathy, and should be given equal attention because they also determine the outcomes of innovation (Csikszentmihalyi, 1988).

2.2. The role of empathy in innovation

Empathy has been considered to be the core value and ability in user-centered design (Rusmann et al., 2022). Some empirical studies have indicated a positive association between empathy and innovation (Chang et al., 2022; Johnson et al., 2014). Johnson et al. (2014) conducted design projects using empathic experience design to improve user-centered creative idea generation. Their results showed that empathic design led to higher originality and lower design fixation.

Moreover, experience-driven empathy can immerse designers in users' real environments, thus promoting designers' innovation (Chang et al., 2022). Other studies have suggested that incorporating empathy into the design thinking process can promote entrepreneurs' innovation and design sensibility (Lee et al., 2021). Overall, previous studies have provided strong evidence of the positive relationship between empathy and innovation. In user-centered design, designers need to develop empathy with the potential users for whom they are designing the products or services (Cardoso et al., 2016). Better empathy will increase the likelihood that the designed product or service will meet users' needs or requirements (Kouprie et al., 2009) and will thus improve the applicability, acceptance, and adoption of the end design (Wilkinson de al., 2014).

In summary, empathetic design thinkers notice problems or needs that others do not and use their insight to inspire design innovation (Cardoso et al., 2016). Based on the aforementioned evidence, we hypothesize a positive relationship between empathy and innovation:

H1. *Empathy positively predicts innovation.*

2.3. The mediating role of motivation

Motivation is identified as the direction and magnitude of behavior, or as "what goals people choose to pursue and how actively or intensely they pursue them" (Keller, 2010, p. 22).

Keller (2010) proposed the ARCS model, which features four motivational aspects: attention, pertinence, trust, and fulfillment. Motivation can be generated when the learning activities attract entrepreneurs' attention, are relevant to their learning goals, and make them feel confident and satisfied when accomplishing their learning tasks (Keller, 2010; Ceptureanu et al., 2025).

The literature has shown that motivation is a well-established contributor to innovation (Benedek et al., 2020). When individuals are motivated, especially intrinsically, their curiosity and interest will extend their scope of attention and the cognitive information available. This encourages their cognitive flexibility and persistence with complex and challenging tasks or problems, thus stimulating greater innovation (Grant et al., 2011). A meta-analysis by Liu et al. (2016) revealed that different elements of motivation functioned differently as predictors of innovation and suggested the need for a more fine-grained theory to explain the complex relationship between motivation and innovation. Some empirical studies have proved that there is a positive association between empathy and motivation (Longobardi et al., 2020). This may be because individuals have higher altruistic motivation when they are empathizing. That is, empathic individuals will be motivated to alleviate the suffering of others and meet the needs of others (Van Lange, 2008). Therefore, we posit that motivation mediates the relationship between empathy and innovation, and we explore the deeper mediating effects of motivation in terms of attention, pertinence, creative trust, and fulfillment.

2.3.1. Attention in motivation

As an aspect of motivation, attention refers to capturing the interest of entrepreneurs and stimulating their curiosity to learn (Keller, 2010). Entrepreneurs will be more curious about a task if they devote more attention to it (Keller, 2010). Curiosity has been widely confirmed as a positive predictor of innovation (Schutte et al., 2020). Csikszentmihalyi (1988) found that learners who devote sufficient time and effort or who focus a large amount of attention on their tasks are more likely to be creative and original. Besides, Keller (2010) stated that deeper levels of curiosity and attention can be stimulated by more complex problem-solving situations. As is known, design tasks usually involve solving ill-structured problems (Stewart, 2011). Such challenging design problems can stimulate entrepreneurs' interest and attract their attention (Stewart, 2011). Therefore, in this study, entrepreneurs' attention to design tasks may be a positive predictor of their innovation.

Considerable empirical evidence has been found that entrepreneurs tend to lack attention when their needs and feelings are not considered or when they are taught in a monotonous delivery style (Rana et al., 2019). Instead, empathy may be an appropriate way to stimulate and maintain entrepreneurs' interest and attention by asking them to take on the perspective of other people and to try to experience their emotions and thoughts (Håkansson et al., 2003). Specifically, the empathizing process during design practice includes discovery, immersion, connection and detachment (Kouprie et al., 2009).

In the discovery phase of empathizing, stepping into users' worlds can increase designers' curiosity as well as their willingness and motivation to understand users (Kouprie et al., 2009). In this way, entrepreneurs will become immersed in the tasks and materials, thus improving their innovation (Klapwijk et al., 2015). Therefore, the following hypothesis is formulated:

H2a. *Empathy is positively related to attention.*

H2b. *Attention is positively related to innovation.*

2.3.2. Pertinence in motivation

A sense of pertinence in motivation occurs when the content to be learned is perceived to be useful or meaningful to one's work or life (Keller, 2010). Theoretically, using the ARCS model, Keller (2010) found that entrepreneurs will perform better when the learning task is related to their lives or local communities (Keller, 2010). Many recent studies have sought to improve entrepreneurs' innovaiton by using design tasks that are related to

entrepreneurs' real-life experiences and are meaningful or significant to them (Kao et al., 2017).
In addition, Klapwijk et al. (2015) further indicated that designing relevant and meaningful tasks not only stimulates entrepreneur designers' innovation but also positively relates to their empathic ability by allowing them to immerse themselves in and experience the context for which the products were designed in the early phases of the design process. In particular, this immersion would enable entrepreneurs to make connections with users and recall their own similar experiences, which is an indispensable component of empathy (Kouprie et al., 2009).
Therefore, this study proposes the following hypothesis:
H3a. *Empathy is positively related to pertinence.*
H3b. *Pertinence is positively related to innovation.*

2.3.3. Creative trust in motivation
Trust in the innovation context is called creative trust, which has been identified as entrepreneurs' perceptions of their trust or belief that they can generate creative ideas or innovation (Liu et al., 2017). Some studies have found that creative trust is significantly related to creative performance or creative idea/product generation (Huang et al., 2020). Individuals with higher creative trust will be more likely to engage in creative tasks, perform creatively, make sustained efforts to address challenging or difficult tasks, and achieve a higher level of creative performance (Beghetto et al., 2017).
One of the main goals of design thinking is to develop designers' creative trust (Carroll et al., 2010), in which empathy plays an important role (Voigt et al., 2019). Design thinking as a framework is conducive to creative trust. That is, the design thinking framework allows entrepreneurs to transfer the process of design into their own mindsets. With iteration process, design thinking can help learners to complete creative design tasks more easily.
As such, their creative trust can be improved by this process (Voigt et al., 2019). Moreover, empathy, as the essential step in design thinking is helpful to stimulate entrepreneurs' attention and interest and maintain their engagement; thus, it should be a positive predictor of creative trust. Therefore, we formulate the fourth research hypothesis:
H4a. *Empathy is positively related to trust.*
H4b. *Trust is positively related to innovation.*

2.3.4. Fulfillment in motivation
Keller (2010) indicated in the ARCS model that individuals will be motivated to learn in the initial stage when the task is interesting and captures their attention and the context is related to their lives. However, individuals usually need to make a sustained effort to achieve success in solving complex design tasks. In

this case, fulfillment plays an important role in maintaining motivation (Hasegawa et al., 2015). Previous research has confirmed that fulfillment is significantly correlated with innovation (Robinson et al., 2010). Amabile et al. (1986) indicated that intrinsic interest was correlated with innovation because of individuals' enjoyment and fulfillment (Amabile et al., 1986).
A significant correlation has been found between empathy and fulfillment (Silva et al., 2019). Some studies have suggested that empathy increases compassion fulfillment for leading individuals to feel "strengthened by having been able to help, satisfied with one's situation, and developed as a person" (Hansen et al., 2018, p. 632). Hence, the mediating role of fulfillment is hypothesized:
H5a. *Empathy is positively related to fulfillment.*
H5b. *Fulfillment is positively related to innovation.*

The current study investigates the mechanisms underlying the relationships between empathy, motivation, and innovation. An explanatory model (Figure 1) is proposed to investigate the mediating effects of motivation in terms of attention, pertinence, trust, and fulfillment.
A 27-item questionnaire was used to collect data, and partial least squares structural equation modeling (PLS-SEM) was used to test the explanatory model. Therefore, the innovation measured using a questionnaire in our study focused on the creative person or personality.

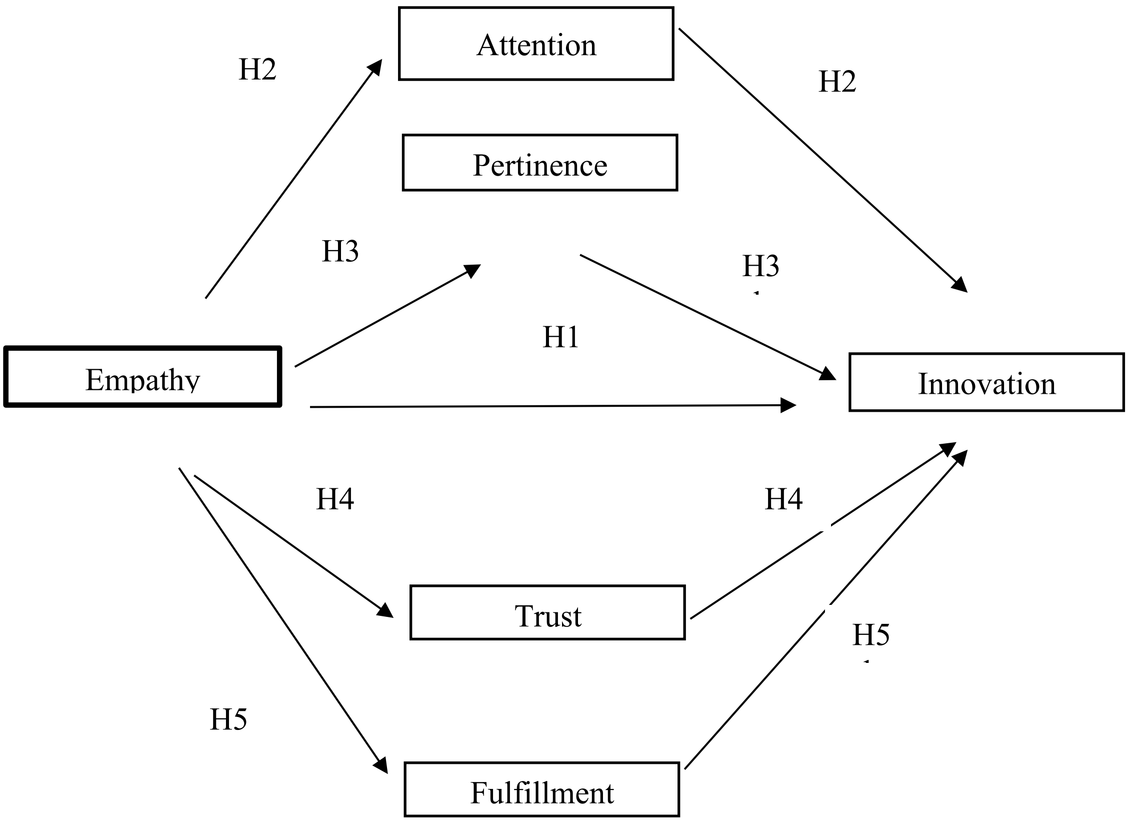


Figure 1. Proposed research model

3. Method

3.1. Participants and procedure

The data reported in this study were collected in from November 2024 to September 2025. The participants were 247 entrepreneurs, including 134 male (54.2%) and 113 female (45.8%) entrepreneurs. Their average age was 42.65. The participants signed a consent form before the commencement of the study. Before data collection, the entrepreneurs had no relevant experience in design thinking. A pretest questionnaire was administered to collect the entrepreneurs' age and gender information where the entrepreneurs were asked to complete a design task- designing a creative innovation facility.

3.2. Measurements

3.2.1. Entrepreneurs' perceptions of their empathic ability

The entrepreneurs' perceptions of their empathic ability were measured by three items from the Toronto Empathy Questionnaire (TEQ) (Spreng et al., 2009). The participants responded to each statement on a 5-point Likert-type scale, ranging from 1 = *totally disagree* to 5 = *totally agree*. An example item is "If I were a designer, I would be very concerned about the user's preferences and feelings when designing a product." The reliability of the scale was acceptable (Cronbach's α = 0.724). The TEQ has been widely used to test participants' empathy (Harley et al., 2020). Harley et al. (2020) found that the general empathic tendency measured by the TEQ was positively and significantly correlated with participants' task empathy.

3.2.2. Motivation in design tasks

Motivation was measured by 10 items adapted from the Course Interest Survey developed by Keller (2010), which has high reliability and validity. An example item for attention is "My curiosity is stimulated by the questions asked or the problems to be solved in developing business opportunities." An example item for pertinence is "The things I am learning in this course will be useful to me." The items for trust were adopted from the Competency-Based Creative Agency Scale by Leifer et al. (2014), which includes items such as "Share your work with others before it is finished". An example item for fulfillment is "I enjoy working for me." Responses were scored on a 5-point Likert scale ranging from 1 = *Not True* to 5 = *Very True*. In the current study, the Cronbach's α values for attention, pertinence, trust and fulfillment were 0.91, 0.77, 0.38 and 0.82, respectively.

3.2.3. Self-perceived innovation

The Williams Creativity Assessment Packet was used to measure the participants' innovation (Williams, 1980). We selected 10 items that are appropriate for entrepreneurs. However, only five items met the loading factor criterion. Each statement was scored on a 5-point Likert scale, ranging from 1 = *definitively disagree* to 5 = *definitively agree*. A sample item is "There are many things I'd like to try by myself." Cronbach's α for the innovation scale was 0.77. Note that although assessment scales for creative products or creative activities have been widely used to measure innovation, they are group-level measures rather than individual- level measures.

4. Data analysis and results

To test the proposed model and aforementioned hypotheses, we applied PLS-SEM using Smart PLS software version 4.1.1.2. (Ringle, 2015), which is suitable for predictive analyses in complex models (Hair et al., 2022). Specifically, we tested the hypothesized model in two steps. First, we built a measurement model to examine its reliability and validity. Second, we built a structural model to measure the path coefficients. To further reveal the mediating effects of attention, pertinence, trust, and fulfillment in motivation, bootstrap analysis, a rigorous and powerful mediation test, was used, with a resample of n = 5,000 and a 95% trust interval (Preacher et al., 2008).

4.1. Descriptive statistics and correlations between the variables

Table 1 shows the descriptive statistics and correlation coefficients for all of the variables. As expected, all six variables were correlated.

4.1.1 Assessment of the structural model

The convergent validity of the measurement model was evaluated using the reliability of each item, the composite reliability (CR) of the measured constructs, and the average variance extracted (AVE) (Fornell et al., 1981). When Cronbach's α and CR values are greater than 0.7 and the AVE is greater than 0.5, convergent validity is sufficient (Fornell et al., 1981). As shown in Table 2, all of the constructs met these requirements, suggesting that measurement model had good convergent validity at the construct level. The factor loadings were all acceptable, thus indicating adequate validity according to the threshold value of 0.5 by Hair et al. (2006).

Additionally, the discriminant validity of this model was assessed using the Fornell–Larcker matrix. A research model would have sufficient divergent validity if the parameter indicates that each variable explains more of the variance of its indicators than the indicators of the other constructs (Fornell et al., 1981). The results in Table 3 show that for all six variables, the matrix diameter was larger than the other arrays of each variable.

Table 1. Descriptive statistics, including the means, standard deviations and correlations between empathy, trust, reference, attention, fulfillment and innovation.

	1	2	3	4	5	6	Mean	SD
1. Empathy	1.00	4.15	0.69					
2. Attention	0.42**	4.26	0.83					
3. Reference	0.38**	0.79**	4.23	0.82				
4. Trust	0.42**	0.38**	0.36**	3.74	0.83			
5. Fulfillment	0.36**	0.73**	0.66**	0.40**	4.34	0.79		
6. Innovation	0.43**	0.51**	0.52**	0.49**	0.40**	1.00	3.38	0.48

Note. $^{*}p < .05$; $^{**}p < .01$

Table 2. The convergent validity and reliability of the measures

Measure	Item	Loadings	Cronbach α	CR	AVE

Empathy	3	0.74–0.84	0.70	0.82	0.62
Attention	3	0.89–0.91	0.89	0.92	0.83
Pertinence	2	0.88–0.902	0.75	0.88	0.79
Trust	5	0.64–0.82	0.81	0.86	0.56
Fulfillment	2	0.89–0.91	0.80	0.90	0.83
Innovation	5	0.60–0.76	0.75	0.83	0.51

Note. CR = the composite reliability; AVE = average variance extracted

Table 3. Discriminant validity using the Fornell–Larcker matrix

Measure	Empathy	Attention	Pertinence	Trust	Fulfillment	Innovation
Empathy	0.78					
Attention	0.42	0.88				
Pertinence	0.39	0.79	0.88			
Trust	0.43	0.38	0.36	0.75		
Fulfillment	0.36	0.73	0.66	0.40	0.88	
Innovation	0.44	0.51	0.52	0.51	0.41	0.71

Note. Highlighted values are squared inter-construct correlations for the Fornell–Larcker criterion

4.2. Structural model and hypothesis testing

4.2.1. Direct effects

In light of the direct effects posited in the model, H1, “empathy is the predictor of innovation” was corroborated. The participants with higher levels of empathy also showed higher levels of innovation (β = 0.14. *p* = .007). Moreover, as shown in Figure 2; Table 4, H2, H3, and H4 were supported. Entrepreneurs with higher levels of empathy also reported higher attention (β = 0.42, *p* < .001, H2a), pertinence (β = 0.39, *p* < .001, H3a) and trust (β = 0.43, *p* < .001, H4a). In addition, their innovation was predicted by attention (β = 0.16, *p* = .044, H2b), pertinence (β = 0.24, *p* = .002, H3b), and trust (β = 0.28, *p* < .001, H4b). H5 was partially supported. Although higher empathy was found to predict higher fulfillment (β = 0.36, *p* < .001, H5a), a higher fulfillment level was found to be negatively related to innovation (β = − 0.08, *p* = .172, H5b).

Table 4. Results for the direct effects

Hypothesis	Path	Standardized β	SE	*p-value*	Decision
H1	Empathy → Innovation	0.14^{**}	0.06	0.007	Supported

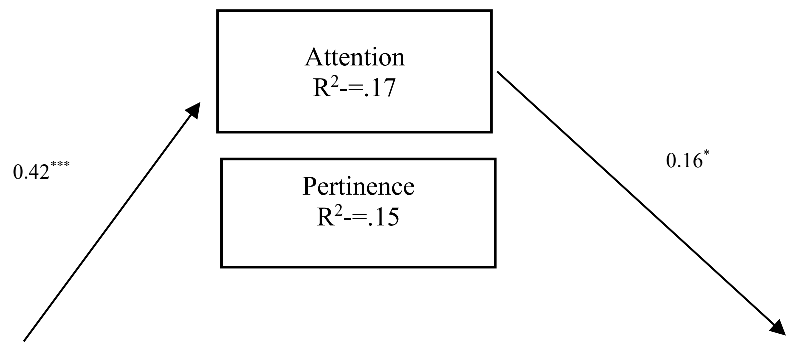
H2a	Empathy → Attention	0.42^{***}	0.07	< 0.001	Supported
H2b	Attention → Innovation	0.16^{*}	0.11	0.042	Supported
H3a	Empathy → Pertinence	0.39^{***}	0.07	< 0.001	Supported
H3b	Pertinence → Innovation	0.24^{**}	0.09	0.002	Supported
H4a	Empathy→ Trust	0.43^{***}	0.07	< 0.001	Supported
H4b	Trust → Innovation	0.28^{***}	0.09	< 0.001	Supported
H5a	Empathy → Fulfillment	0.36^{***}	0.08	< 0.001	Supported
H5b	Fulfillment → Innovation	− 0.08	0.10	0.172	Not supported

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

4.2.2. Indirect effects and mediating effects

As shown in Figure 2, the explained variances (R^2) of attention, pertinence, trust, and fulfillment were 0.17, 0.15, 0.20, and 0.13, respectively. In general, the R^2 of innovation was 0.43, revealing that all of the variables of the research model explained 45% of innovation.

As Table 5 shows, the 95% trust intervals of the indirect paths for attention (95% CI = [0.002, 0.14], β = 0.07, *p* = .044), pertinence (95% CI = [0.04, 0.16], β = 0.09, *p* = .002), and trust (95% CI = [0.04, 0.18], β = 0.10, *p* < .001) did not include 0, suggesting significant mediating effects. However, the *p*-value for the indirect path from empathy to innovation through fulfillment (95% CI = [-0.09, 0.04], β = − 0.03, *p* = .182) was greater than 0.05, implying that the mediating effect of fulfillment was not supported. Therefore, H2, H3, and H4 were supported and H5 was rejected. In other words, attention, pertinence, and trust had significant mediating effects on the relationship between empathy and innovation, and fulfillment did not. Moreover, trust was found to have the greatest explanatory power in the mediating effects between empathy and innovation. The total effect of empathy on innovation was also significant and positive (95% CI = [0.21, 0.34], β = 0.26, *p* < .001).



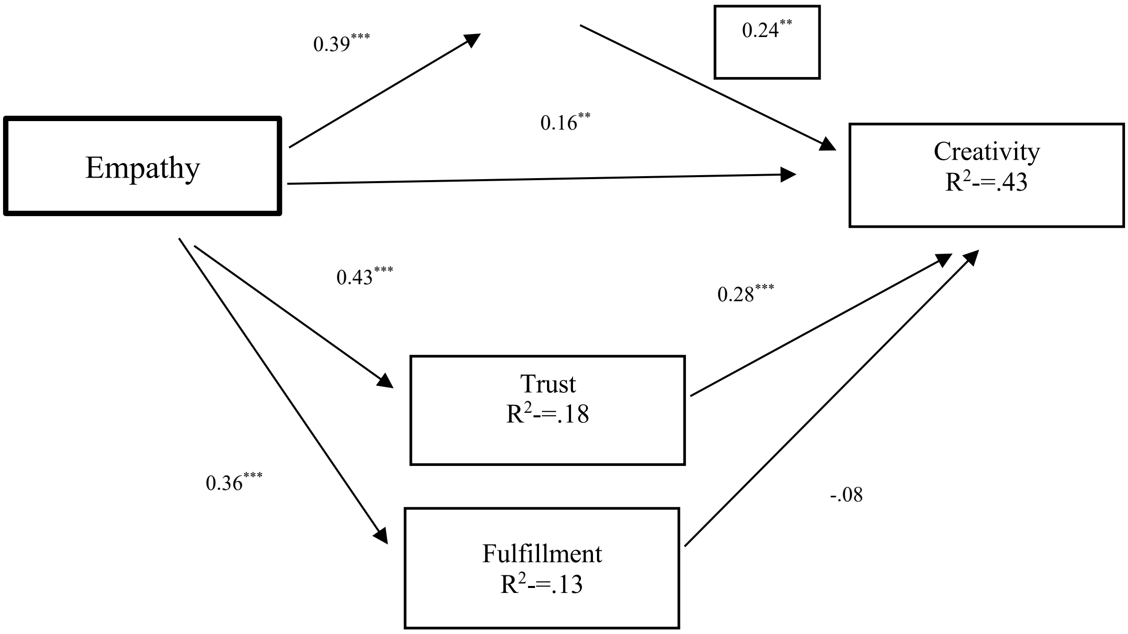


Figure 2. Proposed research model Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

6. Discussion

The study explored the mechanisms by which empathy and motivation affect innovation in design and the mediating effects of the four aspects of motivation on empathy and innovation based on Keller's ARCS model. The results indicate that entrepreneurs with higher level of empathy are more likely to be motivated and to achieve a higher level of innovation in the design thinking process.

6.1. The effect of empathy on innovation

The results confirm that empathy is a significant predictor of innovation, directly or indirectly, consistent with previous research (Lee et al., 2021). Demetriou et al. (2022) showed that entrepreneurs who received empathy instruction in design tasks showed higher levels of emotional and cognitive creativity. Empathic individuals usually have high environment sensitivity, which is the ability to notice and identify others' feelings accurately (Carlozzi et al., 1995). In addition, more empathic people are more open-minded and less dogmatic, so they can more easily accept incoming messages and then discover the real problem or user needs (Carlozzi et al., 1995). Thus, they are more likely to produce more creative products with greater usefulness (Demetriou et al., 2022).

Table 5. Results for the indirect effects and mediating effects

Path	SE	Bias-corrected 95%CI

	Standardized β		Lower	Upper	p-value
Empathy → Attention → Innovation	0.07*	0.05	0.002	0.14	0.044
Empathy → Pertinence → Innovation	0.09**	0.04	0.05	0.16	0.002
Empathy → Trust → Innovation	0.10***	0.04	0.06	0.18	< 0.001
Empathy → Fulfillment → Innovation	− 0.03	0.04	-0.09	0.03	0.182
Total	0.26***	0.05	0.21	0.34	< 0.001

Note. CI = bias-corrected bootstrap confidence interval
*$p < .05$; **$p < .01$; ***$p < .001$

6.2. The mediating effect of motivation

The results for the significant indirect effects and mediating effects indicate that motivation plays an important role in the relationship between entrepreneurs' empathy and innovation.

First, the findings reveal that both empathy and motivation are significantly positively related to innovation, which is in line with previous research (Csikszentmihalyi, 1988; Grant et al., 2011; Lee et al., 2021). Second, motivation was shown to strengthen the relationship between empathy and innovation. A plausible explanation for these findings could be Kouprie et al. (2009) findings, which states that intrinsic motivation can be catalyzed. Empathy may be an important stimulator of intrinsic motivation, which may promote innovation because motivated people are more open and more willing to exert sustained effort on new ideas and challenges.

6.2.1. The mediating effect of attention in motivation

The results show that attention in motivation is a significant mediator of the relationship between empathy and innovation, which is consistent with previous research (Ceptureanu et al., 2026). Empathy in the design thinking process is beneficial for maintaining entrepreneurs' attention in solving design tasks (Kouprie et al., 2009). That is, keeping users' needs in mind, entrepreneurs will put sustained effort into addressing design challenges. Then, sustained attention and effort will stimulate new idea generation and innovation (Demetriou et al., 2022).

6.2.2. The mediating effect of pertinence in motivation

The mediating effect of pertinence in motivation on the relationship between empathy and innovation is supported. This indicates that entrepreneurs with higher levels of empathy are more likely to perceive the pertinence of tasks or consider them to be more meaningful and useful. Perceived pertinence or usefulness will stimulate entrepreneurs' innovation during the design thinking process. Empathy and innovation can be improved when the design task is relevant to learners' real lives. Therefore, to promote innovation in design thinking, it is necessary to enable entrepreneurs to perceive the pertinence of the tasks to their lives.

6.2.3. The mediating effect of creative trust in motivation

This study shows that of the four aspects of motivation, trust is the greatest contributor to innovation and the mediating variable with the greatest effect on the relationship between empathy and innovation. Therefore, creative trust in motivation is the essential psychological mechanism behind empathy and innovation. This finding is consistent with self-determination theory and previous research, which suggests that entrepreneurs with higher levels of trust perform better in learning and innovation (Gong, 2009; Liu et al., 2017). In other words, creative trust may promote innovation (Leifer et al., 2014). Moreover, entrepreneurs become more confident after they experience design and empathy activities in design thinking (Leifer et al., 2014). Because entrepreneurs' empathy experiences will enable them to feel more competent in completing the design tasks for users and more confident in the design solution to meet user need. Therefore, when designers develop better empathy with users or a deeper understanding of user needs, they become more confident with their creations (Voigt et al., 2019).

6.2.4. The nonsignificant mediating effect of fulfillment in motivation

Although empathy has been confirmed as a positive precursor of fulfillment in motivation, the mediating effect of fulfillment on innovation is not significant. However, our results indicate that entrepreneurs with higher levels of empathy are more likely to be satisfied with the task process, which is in line with previous research (Hansen et al., 2018; Wagaman et al., 2015). Fulfillment is a feeling and attitude generated after comparing learning outcomes with those of others or the expectations of the entrepreneurs or employees (Keller, 2010). Motivation includes intrinsic motivation and extrinsic motivation. The generally accepted viewpoint is that intrinsic motivation is conducive to innovation but that extrinsic motivation has a detrimental and undermining effect on intrinsic motivation and innovation (Ceci et al., 2016). Therefore, the finding of the non-significant effect of fulfillment on innovation may be because the extrinsic factors of fulfillment in Keller's ARCS model are detrimental to innovation. This result is in line with previous research. Entrepreneurs' intrinsic motivation and innovation would be undermined when the task is regarded as a means to achieve the extrinsic motivation such as expected reward, expected evaluation, competition, surveillance, and restricted choice (Amabile et al., 1986; Hennessey et al., 2010).

7. Conclusions, limitations and implications

The non-rational dimensions of innovation, motivation and empathy have received increasing interest in recent years. However, most previous research has focused on the direct effects of empathy and motivation on innovation (Lee et al., 2021; Woo et al., 2018). Little is known about how empathy and motivation work in synergy with innovation. To explore the underlying mechanisms of stimulating innovation during the design thinking process, this study took both motivation and empathy into consideration. A structural equation model including all of these variables was developed to test our hypotheses.

This study further examined the mediating effects of motivation, including attention, pertinence, trust, and fulfillment. We found that attention, pertinence, and trust were confirmed to be significant mediating factors in the relationship between empathy and innovation. These explorations extend previous research on the direct effects of empathy and innovation. This research contributes to the emerging literature on design thinking and provides initial insights into the role that empathy plays in user-centered design. The current study has several limitations.

First, the five variables in our research model only explained 45% of the variance in innovation, suggesting that other variables that were not included in this study may influence innovation. In light of the literature, such variables may include personal and contextual characteristics (Shalley et al., 2004) and assessment strategies (Zhou et al., 2001). Therefore, more factors should be explored in the future.

Second, this study measured entrepreneurs' innovation with the self-reported questionnaire, which measures personal characteristics or tendencies. More objective evaluation of entrepreneurs' innovation in design thinking is needed, such as of product innovation or process innovation.

Therefore, future studies should examine the relationship between empathy and product or process innovation. *Finally*, this study only examined the relationships between the variables. In the future, (quasi-) experimental methods should be used to make causal inferences.

Despite these limitations, our findings have a number of practical implications. *First*, this study indicated the importance of design thinking and empathy in the development of innovation. Thus, entrepreneurs should pay more attention to the social-emotional skill of empathy.

Deeper empathy with users can promote the design of more meaningful and useful products or solutions rather than trivial and useless things (Demetriou et al., 2022). It has been recognized that "empathy can ignite and infuse the creative process to make the product real, usable and meaningful to the user" (Demetriou et al., 2022, p.5).

Second, appropriate strategies are needed to stimulate learners' motivation. Ryan et al. (2000) suggested that consultants' autonomy support is indispensable for improving entrepreneurs' motivation. As shown by the current study, empathy, attention, pertinence, trust, and fulfillment all can be referable aspects of consultants' autonomy support to ignite and sustain entrepreneurs' motivation.

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