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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.

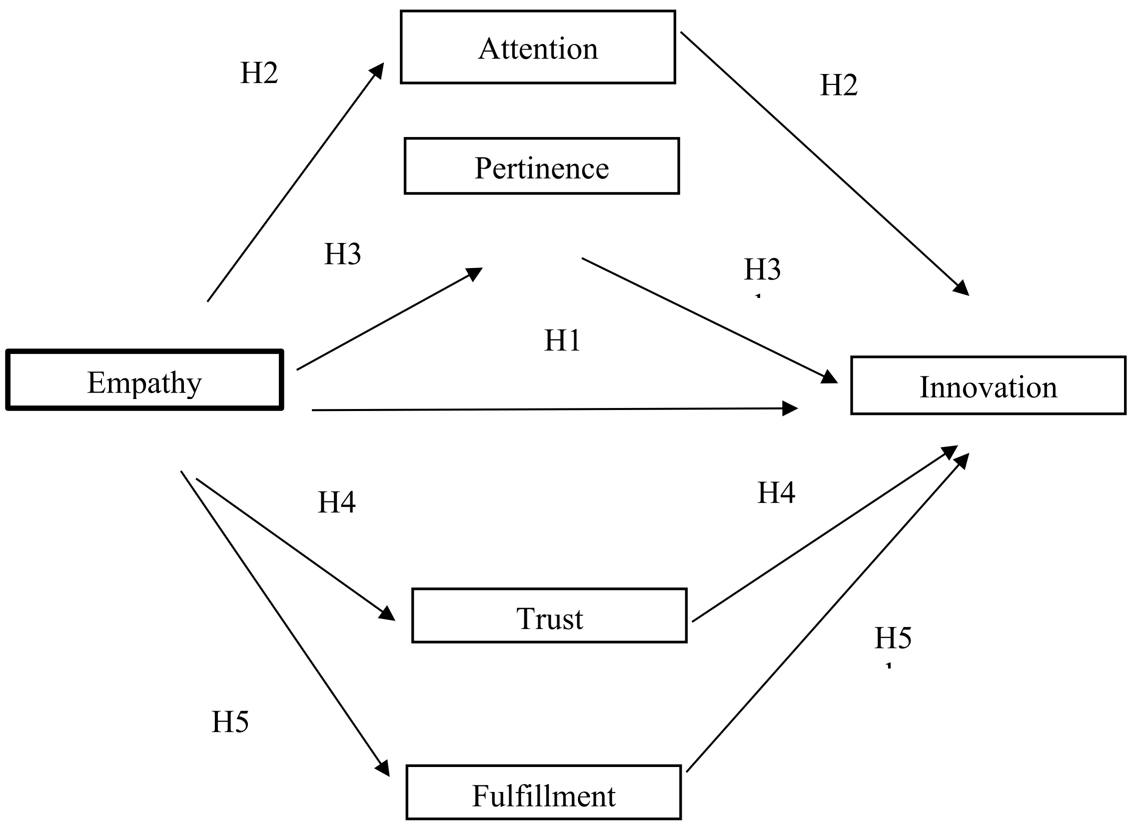

Figure 1. Proposed research model

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 = 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 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 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 □ 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 □	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 ($\beta = 0.14$. $p = .007$). Moreover, as shown in Figure 2; Table 4, H2, H3, and H4 were supported. Entrepreneurs with higher levels of empathy also reported higher attention ($\beta = 0.42$, $p < .001$, H2a), pertinence ($\beta = 0.39$, $p < .001$, H3a) and trust ($\beta = 0.43$, $p < .001$, H4a). In addition, their innovation was predicted by attention ($\beta = 0.16$, $p = .044$, H2b), pertinence ($\beta = 0.24$, $p = .002$, H3b), and trust ($\beta = 0.28$, $p < .001$, H4b). H5 was partially supported. Although higher empathy was found to predict higher fulfillment ($\beta = 0.36$, $p < .001$, H5a), a higher fulfillment level was found to be negatively related to innovation ($\beta = - 0.08$, $p = .172$, 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).

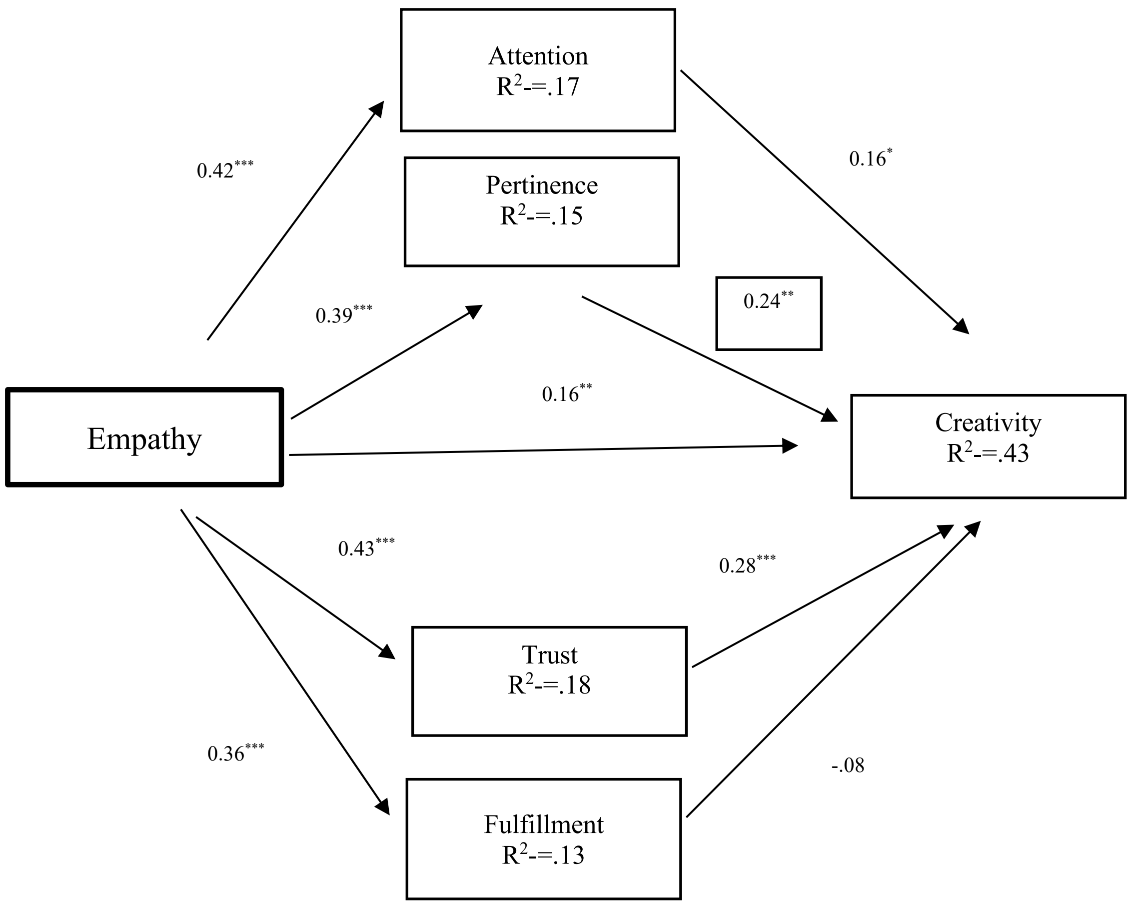

Figure 2. Proposed research model Note. **p* < .05; ***p* < .01; ****p* < .001

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	Standardized	SE	Bias-corrected 95%CI		
			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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META-HEURISTICS FOR RENEWABLE ENERGY RESIDENTIAL COMMUNITIES DETECTION

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Abstract

Metaheuristics are high-level heuristic strategies that guide the behaviour of subordinated heuristics to solve optimization problems. This paper proposes a population-based metaheuristic approach for the detection of cost-efficient renewable-based residential energy communities. The problem is formulated as an optimization model minimizing total operational costs through coordinated photovoltaic generation and energy storage systems. Particle Swarm Optimization (PSO) is employed to efficiently explore the large combinatorial space of candidate communities. Results on a residential case study show that PSO achieves near-optimal solutions comparable to Monte Carlo-based benchmarks, while reducing computational time.

Keywords: metaheuristics; energy communities; renewable energy.

1. Introduction

Renewable energy is gaining more and more importance for different classes of stakeholders such civil society, industry, policy makers, and academics. The deployment of many publicly funded initiatives that encourage the Twin transition (i.e., integrating green and digital transition) witness this aspect at the policy makers stage, whilst many firms have introduced ESG-related concepts to (also) drive productivity and profitability. From the policy makers perspective, this led to an increased attention to address the climate change, to enhance energy security, and to support sustainable economic development. Many contributions highlight the fact that large-scale deployment of renewable energy technologies (i.e., solar, wind, and hydroelectric power) is essential to achieve substantial reductions in greenhouse gas emissions and to meet international climate targets [19, 9]. Moreover, renewables sources are increasingly recognized for their potential to foster technological innovation, to reduce dependence on fossil fuel imports, and to promote resilient energy systems [16]. Also renewable energy related aspects are gaining attention, such as the relation between declining costs of renewable technologies and competitiveness, making renewable sources a key pillar of future energy transitions across both developed and emerging economies [10].

In this context, a key concept is given by energy communities, that can be defined as networks where people have ownership (or can influence the management) of renewable energy sources [17, 18, 14]. The literature analyzes both the technology used by energy communities and the increased efficiency triggered by their deployment. As for the first aspect, these communities are reported to use different technologies for generating, storing, sharing, and managing renewable energy: these include distributed sources, solar photovoltaic systems, and small-scale wind turbines, often combined with storage systems to mitigate intermittency and enable energy autonomy. In this context, Microgrids, Smart metering, and Information and Communication Technologies (ICT) support efficient local distribution, monitoring, and technical integration [7]: advanced energy system modelling and optimisation tools help design community operations, incorporating diverse business models and objectives [1].

As for the second aspect, energy communities that embed renewable energy sources have demonstrated significant potential in enhancing overall energy efficiency within local systems, leading to optimized resource utilization and reduced transmission losses [13]; Moreover, also non-financial outcomes have been investigated, since they can offer affordable energy and im-plement energy efficiency measures targeted at vulnerable households, hence mitigating energy poverty and fostering inclusive participation [8]: empirical studies further indicate that their im-plementation can lead of up a 75% cost reductions through dynamic local balancing of generation and consumption[12]. Of course, the two afore mentioned aspects are intertwined: for instance, blockchain-based platforms are developed to facilitate robust peer-to-peer energy trading, allowing members to directly exchange surplus energy [2].

Anyhow, investigating the effectiveness of such communities triggers the need to resort to multi-objective optimization since many aspects have to be taken into account to determine the optimal community configuration. From a methodological perspective, this problem naturally leads to large-scale combinatorial optimization problems, where exact methods rapidly become computationally infeasible.

In this contribution, we introduce a Meta-heuriostic approach to build energy communities that rely on renewable energy (i.e., solar energy) and compare it with a Montecarlo simulation, in order to show the robustness of the approach and to outline the metaheuristics' improved performances about execution time. Metaheuristics are high-level strategies that coordinate the action of subordinated heuristics to find near-optimal solutions of an optimization problem: they are used when the space to be explored is too huge for being dealt with by an exact methods, and they do not guarantee to find the optimal solution, but a near-optimal one within a reasonable amount of time. This will be useful in our case-study, since an exact solution would lead to the combinatorial explosion, being unable to find the optimal solution in a given time. Please notice that, given the increasing importance witnessed by the private residential sector for the use of solar systems, we are tackling residential units only.

The paper is structured as follows: section 2 will discuss data at hand; section 3 will describe the optimization model, and section 4 will outline the experimental analysis, before concluding in section 5.

2. Our Data

Our set of data comes from observations regarding different consumers' categories, i.e., resi-dential units, small offices, large offices, warehouses, secondary schools, hotels, restaurants and retail strip malls. The afore mentioned categories feature a great variability in demand profiles within the member of temptative energy communities: this can be seen from figure 1, that shows the main statistics of the electricity demand of buildings belonging to Residential Units, Hospitals, Small Offices, and Schools.

In what follows we focus on residential buildings, whose analysis is important to develop effective and sustainable energy management strategies and policies, on top of more and more informed infrastructure planning.[4, 6] The analysis of the other typologies can be found in the appendix.

Our data come from the Open Energy Data Initiative (OEDI) platform, which provides end-use load profiles for the U.S. building stock obtained via calibrated and validated physics-based simulations for multiple residential and commercial building types and end uses, across all U.S.

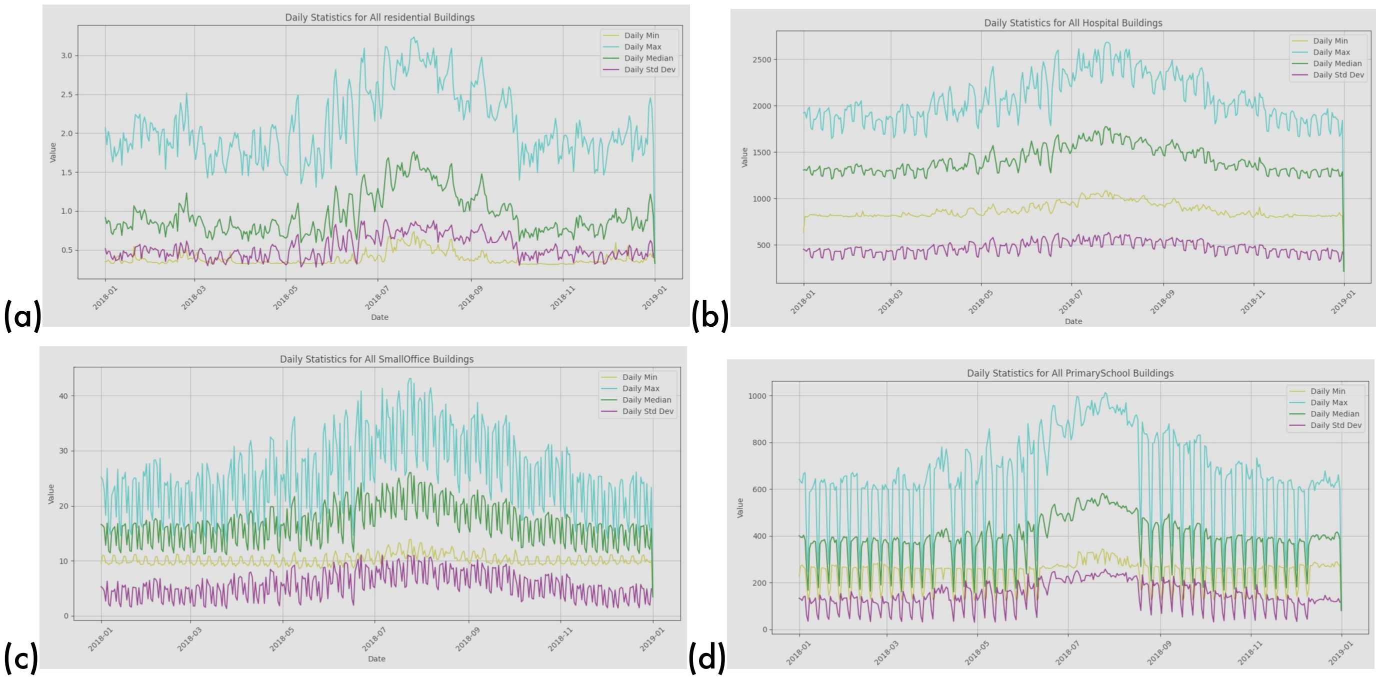


Figure 1: Main statistics of electricity demand of residential buildings(a), hospitals (b), small offices (c), and schools (d)

climate regions. In addition, the dataset includes historical weather information (e.g., humidity, pressure, wind speed and direction, temperature, and solar radiation), which is required to generate consistent PV production profiles [20].

As for residential buildings, we dispose, for each buildings, the following features: Square Footage, i.e., the total floor area of the residential building; Number of Bedrooms, i.e., the total number of bedrooms in the house; Number of Occupants, i.e., the total number of individuals resid-ing in the building; Bath Fan Energy, i.e., the energy consumed by bathroom exhaust fans; Ceiling Fan Energy, i.e., the energy consumed by ceiling fans used for ventilation or cooling; Clothes Dryer Energy, i.e., the energy consumed by the clothes dryer in the residential unit; Clothes Washer Energy, i.e., the energy consumed by the washing machine; Cooking Range Energy, i.e., the energy consumed by the cooking range or stove; Cooling Energy, i.e., the energy consumed by cooling systems; Dishwasher Energy, i.e., the energy consumed by the dishwashers. Total Electricity Energy, i.e., the total electricity consumed by the residential buildings; Exterior Lighting Energy, i.e., the energy consumed by outdoor lighting systems;

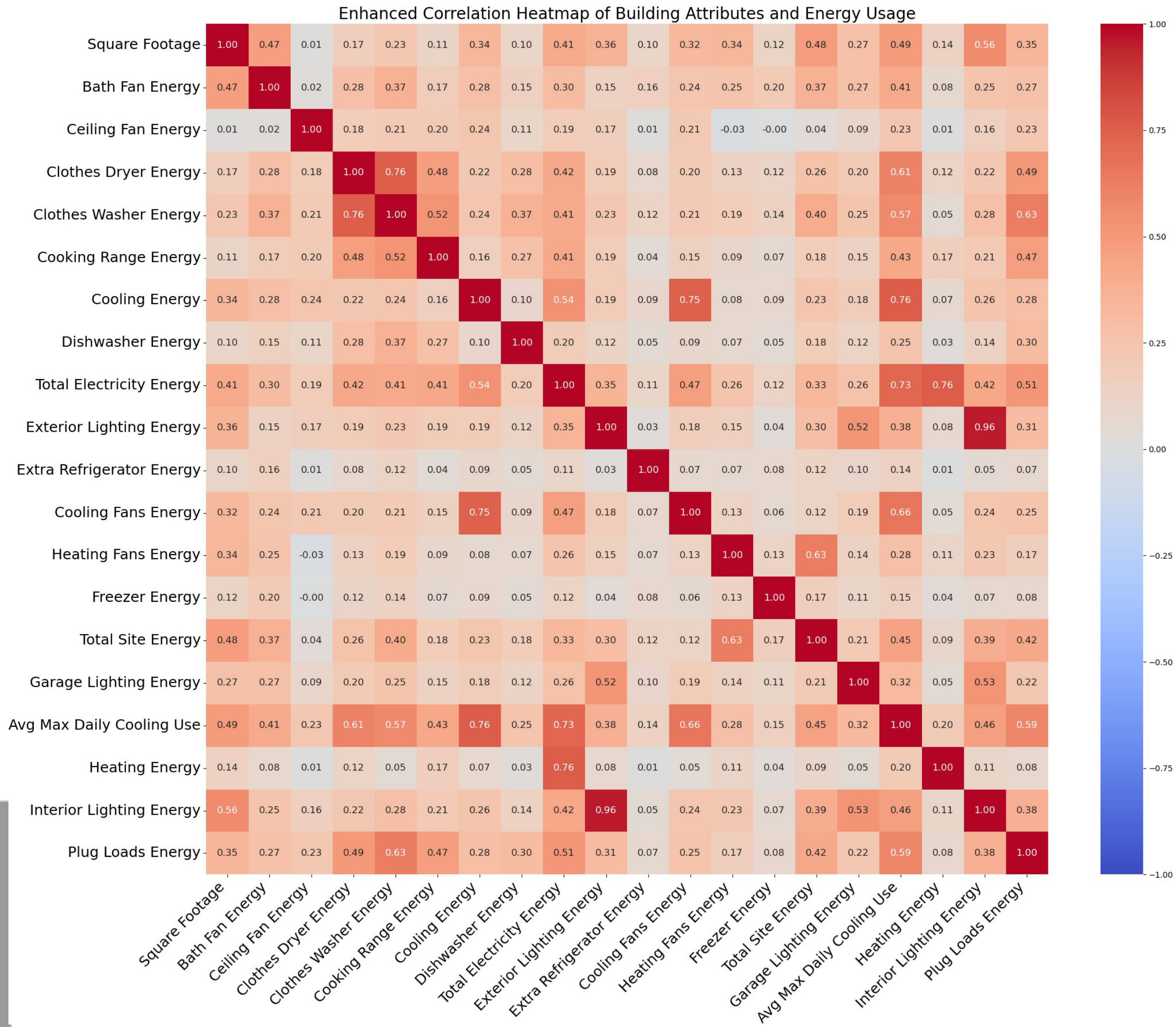
Extra Refrigerator Energy, i.e., the en-ergy consumed by an additional refrigerator; Cooling Fans Energy, i.e., the energy consumed by fans used for cooling purposes; Heating Fans Energy, i.e., the energy consumed by fans used for heating purposes; Freezer Energy, i.e., the energy consumed by standalone freezers; Total Site Energy, i.e., the total energy consumed on-site, including electricity and other sources; Garage Lighting Energy, i.e., the energy consumed by lighting systems in the garage; Avg Max Daily Cooling Use, i.e., the average maximum cooling energy usage per day; Heating Energy, i.e., the energy consumed by heating systems such as furnaces or heat pumps; Interior Lighting Energy, i.e., the energy consumed by lighting systems inside the house; and Plug Loads Energy, i.e., the energy consumed by appliances and electronics connected to electrical outlets.

As a first analysis, we have performed a correlation analysis amongst the different variables over all buildings, whose outcome is reported on the correlation matrix shown in figure 2.

As expected, we found a (moderate) positive correlation between **Square Footage** and **To-tal Electricity Energy** (approximately 0.41), as well as between, **Total Site Energy** and **Square Footage** (approximately 0.48), stressing out that the building size ranges amongst the determinants of the overall energy demand. It can also be seen that there exists a strong posi-tive correlation between **Cooling Energy** and **Total Electricity Energy** (approximately 0.75), showing the energy-intensive nature of air conditioning ; on the contrary, **Heating Energy** ex-hibits a weaker correlation with both **Square Footage** (0.34) and **Total Electricity Energy** (0.30), showing a smaller contribution to overall energy consumption, potentially due to regional climate factors.

Plug Loads Energy and **Interior Lighting Energy** exhibit strong positive correlations with **Total Electricity Energy** (approximately 0.51 and 0.96, respectively). These findings suggest that electrical appliances and lighting are among the dominant electricity consumers in residential buildings. **Dishwasher Energy** and **Clothes Washer Energy** show moderate correlations with **Total Electricity Energy** (around 0.27–0.30), indicating their moderate contribution to overall energy usage. **Cooling Fans Energy** and **Heating Fans Energy** correlate positively with **Total Electricity Energy** (0.47 and 0.45, respectively), showing their significant role in supporting HVAC systems. **Exterior Lighting Energy** displays a moderate correlation with **Total Electricity Energy** (0.35), which reflects its reliance on electrical systems, albeit less than interior lighting.

Figure 2: Correlation matrix between the attributes of residential buildings.



Extra Refrigerator Energy shows a weaker correlation with **Total Electricity Energy** (0.10), indicating that additional refrigeration units have a smaller impact compared to other factors like cooling or lighting. **Garage Lighting Energy** correlates weakly with **Square Footage** (0.27) and moderately with **Total Electricity Energy** (0.22). This suggests a localized impact, likely dependent on garage-specific activities.

3. Our Model

In this contribution, we aim at identifying cost-efficient renewable-based residential energy communities by minimizing the total operational costs through the coordinated use of photo-voltaic (PV) generation and an energy storage system (ESS). In particular, the optimization framework is designed to properly exploit the energy produced by the community's PV system and to manage the ESS so as to store the excess PV generation, assuming equal charging and discharging efficiencies. The total cost of the community includes the electricity purchasing costs from the external grid, together with the operating and maintenance costs of the PV system and the charging/discharging costs of the ESS. Energy export to the main grid is not considered, since all surplus PV production is absorbed by the ESS, whose capacity is treated as a decision variable of the optimization problem. This assumption is consistent with small-scale residential communi-ties where grid export is limited or economically unattractive. This modeling choice promotes the full self-consumption of renewable energy and supports the development of energy communities aligned with the net-zero emission objective. We consider energy communities composed of N residential units, indicated with $i \in \{1, 2, \ldots, N\}$, and we model the system dynamics over hourly time steps $t \in \{1, 2, \ldots, 24\}$. For a given commu-nity size N , the objective is to minimize the total operational cost of the community, defined as the sum of grid electricity costs, ESS costs, and PV generation costs [5]:

$$\min \sum_{t=1}^{24} \left(\sum_{i=1}^{N} C_{i,t}^{Grid} + C_t^{ESS} + C_t^{PV} \right), \tag{3.1}$$

where $C_{i,t}^{Grid}$ denotes the cost of electricity purchased from the external grid by unit i at time t, while C^{ESS} and C^{PV} represent the operational costs associated with the ESS and the PV generation, respectively. These costs depend linearly on the amount of energy drawn from the grid, the energy charged into and discharged from the battery, and the energy produced by the PV system. The ESS is modeled as a battery device that allows the community to temporally shift energy by storing electricity when available and supply it when needed. Let SOC_t denote the state of charge of the ESS at hour t, while E^{cESS} and E^{dESS} represent the energy charged and discharged from the ESS during hour t, respectively. The ESS operation is subject to the following constraints:

$$SOC_{min} \leq SOC_t \leq SOC_{max}, \tag{3.2}$$

$$0 \leq E_t^{cESS} \leq 0.8 \cdot SOC_{max}, \tag{3.3}$$

$$0 \leq E_t^{dESS} \leq 0.8 \cdot SOC_{max}, \tag{3.4}$$

$$SOC_t^{Loss} = \eta_{Loss} \cdot SOC_t, \tag{3.5}$$

$$SOC_t = SOC_{t-1} + E_t^{cESS} \cdot \eta_c - \frac{E_t^{dESS}}{\eta_d} - SOC_t^{Loss}. \tag{3.6}$$

In this formulation, SOC_{max} is a decision variable of the optimization problem representing the maximum storage capacity of the battery, SOC^{Loss} denotes the self-discharge (loss) coefficient of the ESS, and n_c and n_d and are the charge and discharge efficiency parameters, respectively.

Finally, for a fixed number of units N, the system must satisfy the hourly energy balance constraint:

$$\sum_{i=1}^{N} E_{i,t}^{Load} = \sum_{i=1}^{N} E_{i,t}^{Grid} + E_t^{PV} - E_t^{cESS} + E_t^{dESS}, \tag{3.7}$$

where $E_{i,t}^{Load}$ denotes the electricity demand of unit i at time t. This constraint ensures that, at each hour, the total energy demand of the community is met through a combination of grid electricity, photovoltaic generation, and energy storage operations.

4. Our Experimental Setting

As stated in the Introduction, we want to introduce a meta-heuristic approach to the problem identified by [4], and compare it with a Monte Carlo simulation, in order to show the robustness of the approach and to outline the metaheuristics' improved performances about execution time. This section compares the two approaches, by introducing the Montecarlo simulation in section 4.1, and the metaheuristic approach in section 4.2.

4.1. Monte Carlo Simulation

A widely adopted methodology to evaluate the robustness of energy community sizing and operation problems under uncertainty consists in combining the underlying optimization model with a Monte Carlo (MC) simulation scheme. In [5], this approach is employed to jointly capture the stochastic variability of electricity demand profiles and weather-dependent photovoltaic (PV) generation.

The MC framework is structured as follows. At each simulation run, a day is randomly sampled from the reference year, thereby fixing the corresponding solar irradiation profile and the associated PV production. Then, an incremental energy community is constructed by progres-sively aggregating individual load profiles until a target community size N is reached. For each value of N , the resulting optimization problem is solved, and the relevant performance indicators are recorded. Repeating this procedure over a large number of independent replications (typi-cally 1000) allows for the computation of averaged outcomes and statistically robust estimation of system performance. While conceptually straightforward and effective in accounting for uncertainty, this MC-based strategy becomes computationally demanding as the community size increases, since it requires solving the optimization problem a very large number of times. Empirical evidence from the computational experiments on residential energy communities reported in [5] shows that the time required to complete the MC routine grows sharply with N. For small communities, the com-putational effort is limited to a few minutes (approximately 4.10 minutes for $N = 1$ and about 10.05 minutes for $N = 9$), but it reaches about 16.42 minutes at $N = 10$ and about 49.33 minutes at $N = 15$. For larger communities, the total runtime exceeds one hour (approximately 1h04m at $N = 16$, about 1h49m at $N = 24$, and about 1h56m at $N = 25$) and exceeds two hours for $N \geq 26$ (around 2h02m at N = 26-27, peaking at about 2h15m at $N = 28$, and remaining above 2h13m at $N = 30$).

For these reasons, in this work, we propose a meta-heuristic approach aimed at efficiently exploring the large configuration space of candidate communities while preserving robustness and significantly reducing execution times when scaling up the number of units.

To facilitate reproducibility and enable a direct quantitative comparison with our proposed meta-heuristic approach, table 2 reports the numerical results of the residential case study re-ported in [5] and the average computational time required by the Monte Carlo procedure for each selected community size. Specifically, the table collects the values obtained under a fixed PV capacity setting (Panel A) and under a variable PV capacity setting (Panel B), for increasing community size $N \in \{1, 5, 10, 15, 20, 25, 30\}$. IC_N denotes the individual cost of the energy community, defined as the total optimized community cost divided by the number of units N. The quantity SC_N represents the average single-unit cost obtained when the N units are optimized independently. The indicator PS_N denotes the percentage cost savings achieved by the member within the community with respect to the disaggregated configuration. Finally, $IESS_N$ and IPV_N indicate the individual energy storage system (ESS) capacity and the individual photovoltaic (PV) capacity, respectively, obtained by dividing the optimal community-level capacities by the number of units.

The numerical results confirm the main trends discussed in [5] for the residential case study. Under fixed PV capacity (Panel A), individual costs IC_N exhibit a monotonic decrease with the community size, together with increasing percentage cost savings PS_N, which stabilize around 13% for large N. At the same time, the individual ESS capacity $IESS_N$ decreases as N grows, highlighting the capital-efficiency gains induced by aggregation. When the PV capacity is left as a decision variable (Panel B), individual costs are systemati-cally lower than in the fixed-PV case. This effect is accompanied by significantly smaller percentage cost savings, which remain below 4% even for large communities. Moreover, the variable-PV setting leads to larger individual ESS and PV capacities.

Table 1: Residential case-study results reported in [5] for selected community sizes N.

N	1	5	10	15	20	25	30
Panel A: Fixed PV capacity							
IC_N [$]	5.7050	5.2268	5.0686	5.0342	5.0142	5.0227	5.0186
SC_N [$]	5.7050	5.7051	5.6263	5.6240	5.6214	5.6419	5.6478
PS_N [%]	0.0000	10.2564	11.9212	12.4935	12.7813	12.9694	13.1560
$IESS_N$ [kW]	2.6645	1.5411	1.3695	1.2803	1.2376	1.2091	1.1913
Panel B: Variable PV capacity							
IC_N [$]	4.8220	4.7604	4.6882	4.6770	4.6749	4.6864	4.6902
SC_N [$]	4.8220	4.8720	4.8174	4.8123	4.8132	4.8283	4.8336
PS_N [%]	0.0000	2.5305	2.9522	3.0905	3.1374	3.2166	3.2433
$IESS_N$ [kW]	3.6107	3.2009	2.9683	2.9153	2.8874	2.8647	2.8495
IPV_N [kW]	2.4310	2.4405	2.3831	2.3704	2.3606	2.3707	2.3768
Time [min]	4.10	6.01	16.42	49.33	97.62	116.12	133.88

4.2. Meta-heuristic approach

Meta-heuristics are general strategies that guide the action of subordinated heuristics, and can be partitioned into trajectory-based and population-based methods: in the first method, the exploration can be seen as a trajectory over the search landscape; in the latter, as the evolution of a discrete points set. In this contribution we have resorted to the latter class of methods, and implemented Particle Swarm Optimization to solve the problem devised in section 3. Particle Swarm Optimization (PSO), introduced by [11], is a population-based metaheuristic algorithm that gets inspiration from the coordinated movement and information sharing observed in flocks of birds or schools of fish: a swarm of particles explores the search space, with each particle rep-resenting a potential solution. Particles update their positions and velocities iteratively based on their individual best-known position (personal best) and the swarm's global best-known position (global best), enabling collective intelligence to guide the search toward optimal regions. A key strength of PSO lies in its effective mechanism for balancing exploitation (i.e., intensification) to find well performing solutions, and exploration (i.e., diversification), to refine promising areas for higher precision: this adaptive trade-off is facilitated by parameters such as inertia weight and acceleration coefficients, allowing the algorithm to efficiently handle multimodal, non-convex, and high-dimensional optimization landscapes. Several extensions and hybrid variants of PSO have been successfully proposed to address constrained and real-world optimization problems. In particular, hybrid PSO-based approaches have proven effective in financial applications, such as portfolio selection under complex cost structures and constraints, where adaptive penalty mecha-nisms are employed to handle infeasibility and improve convergence properties [3]. These features make PSO particularly effective for complex real-world problems, including those prevalent in finance, such as portfolio selection, risk management, and market forecasting, where objective functions often involve nonlinearity, constraints, and uncertainty.

In our implementation, we have considered a community of N buildings (as defined in Table 2), in which the fitness function is given by Equation 3.1. Each particle in the swarm contains the indicator of a candidate building, and at each iteration, each particle's fitness is evaluated. We track each particle's personal best position (*pbest*) and the global best position (*gbest*), cor-responding to the highest fitness value found so far. After updating, constraints are enforced to ensure feasibility, and this process is iterated for a fixed number of generations or until conver-gence, yielding the final optimal community. More details on the PSO can be sent upon request to the authors.

We can see that our PSO-based meta-heuristic approach leads to comparable results with regard to the Monte Carlo simulation, but a much lower computational time. Indeed, for small-sized instances ($N = 1$, $N = 5$) the results are comparable also with regard to the computational time: this is confirmed by a comparison of the results based on a Wilcoxon signed rank test (tested against a 0.05 significance level), which led us to reject the null hypothesis of difference between the two approaches over the two small sized instances, but not on the others.

5. Conclusions

In this contribution we address the optimization problem investigated in [5] by proposing a metaheuristic-based approach for detecting cost-efficient renewable-based residential energy communities. Specifically, we consider the optimization model for energy community with PV generation and ESS, and we aim at minimizing operational costs by promoting PV self-consumption through storage, with the ESS capacity treated as a decision variable.

Table 2: Residential case-study results obtained by our PSO approach for selected community sizes N .

N	1	5	10	15	20	25	30
Panel A: Fixed PV capacity							
IC_N [$]	5.7050	5.2267	5.5371	4.9914	5.1413	5.0714	5.007
SC_N [$]	5.7054	5.7055	5.6391	5.7194	5.4120	5.6920	5.6570
PS_N [%]	0.0000	10.4733	12.0041	13.4415	12.8178	12.9000	13.1492
$IESS_N$ [kW]	2.6647	1.5674	1.3651	1.0051	1.0615	1.3413	1.1922
Panel B: Variable PV capacity							
IC_N [$]	4.8218	4.7609	4.7251	4.6507	4.5001	4.6023	4.6900
SC_N [$]	4.8223	4.8717	4.6144	4.8375	4.9948	4.9438	4.8609
PS_N [%]	0.0000	2.5304	3.042	3.4162	3.5129	3.3402	3.1945
$IESS_N$ [kW]	3.6107	3.2012	2.8814	3.0143	2.979	2.5790	2.7302
IPV_N [kW]	2.4314	2.4438	2.3914	2.4961	2.5061	2.2987	2.2518
Time [min]	4.32	4.52	5.39	8.25	10.81	13.53	14.07

To deal with the intrinsic combinatorial nature of community detection and the computational burden arising from simulation-based approaches, we compared a standard Monte Carlo routine, which requires solving a large number of optimization scenarios, with a population-based meta-heuristic strategy based on PSO. The computational results on the residential case study highlight that the proposed PSO approach preserves the main economic trends observed under the Monte Carlo benchmark (i.e., cost reductions induced by aggregation), while providing a substantial reduction in computational time as the community size increases. In particular, for the largest community sizes considered, the PSO routine achieves near-comparable performance indicators with execution times that remain within minutes, as opposed to the significantly longer runtime required by the Monte Carlo procedure.

Overall, these findings suggest that PSO-based metaheuristics represent a viable and scalable alternative for energy community detection problems, enabling an efficient exploration of large configuration spaces while maintaining solution quality. Future research directions include extending the framework to multi-objective formulations (e.g., jointly optimizing costs, emissions, and equity metrics), incorporating additional sources of uncertainty, and accounting for energy export and market participation mechanisms.

6. Acknowledgments

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1. Appendix A. Energy conventions and standards in our set of data

Our datasets also include information about the energy conventions applied to various build-ings, where conventions may be instantiated to:

- **ComStock**, which is a highly granular, bottom-up model using multiple data sources, statistical sampling methods, and advanced building energy simulations to estimate the end user hourly energy consumption [15];
- The Database of Energy Efficiency Resources which is referred to as **DEER**;
- The U.S. Department of Energy, which is referred to as **DOE**:.

Depending on their usage, we map all energy conventions to the corresponding standards, that may be instantiated to *Older* (i.e., conventions established before the widespread adoption of modern energy efficiency practices), $M\ id\!-\!range$, (i.e., the ones implemented during a transitional period, developed with stricter efficiency requirements, but still far from the higher efficiency levels mandated by modern standards), and *Modern* (see table A.3 and figure A.3).

This information is also a key feature to measure how the different standards perform in different climate zones: this test would be helpful to assess whether modern standards show an energy savingover all instances: Figg. A.4 and A.5 are helpful to this extent.

The climate zone encoding refers to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard. The encoding *6A* refers to very cold winters, mild summers, high humidity and *6B* to very cold winters, mild summers, low humidity.

Based on the two charts we can observe that in different climate zones the electricity usage of buildings with different standards might not always reflect the intuition where we believe that the modern standards are always using the lowest electricity. In Fig. A.5 it is showcased that the mid-range standards produce lower electricity consumption for the commercial buildings opposed to Fig.A.4.

Table A.3: Convention Mapping

Convention	Standard Type
ComStock DOE Ref Pre-1980	Older Standards
ComStock DOE Ref 1980-2004	Older Standards
ComStock DEER Pre-1975	Older Standards
ComStock DEER 1985	Older Standards
ComStock DEER 1996	Mid-Range Standards
ComStock DEER 2003	Mid-Range Standards
ComStock DEER 2007	Mid-Range Standards
ComStock 90.1-2004	Mid-Range Standards
ComStock 90.1-2007	Mid-Range Standards
ComStock DEER 2011	Modern Standards
ComStock DEER 2014	Modern Standards
ComStock DEER 2015	Modern Standards
ComStock DEER 2017	Modern Standards
ComStock 90.1-2010	Modern Standards
ComStock 90.1-2013	Modern Standards

2. Appendix B. Commercial buildings

As for the commercial buildings, the data are obtained from the OEDI platform [20] partitions buildings belonging to the geographical area of Los Angeles (California) in the following classes:

- LargeOffice, i.e., offices featuring substantial square footage, e.g., corporate headquarters or large-scale administrative facilities.
- PrimarySchool, i.e., primary educational facilities that accommodate young students and host classrooms, administrative offices, cafeterias and gyms, just to name a few.
- Outpatient, i.e., healthcare facilities that provide non-overnight medical services, e.g., diag-nostic imaging and consultations.

- RetailStandalone, i.e., individual retail outlets that are not part of larger shopping centers.

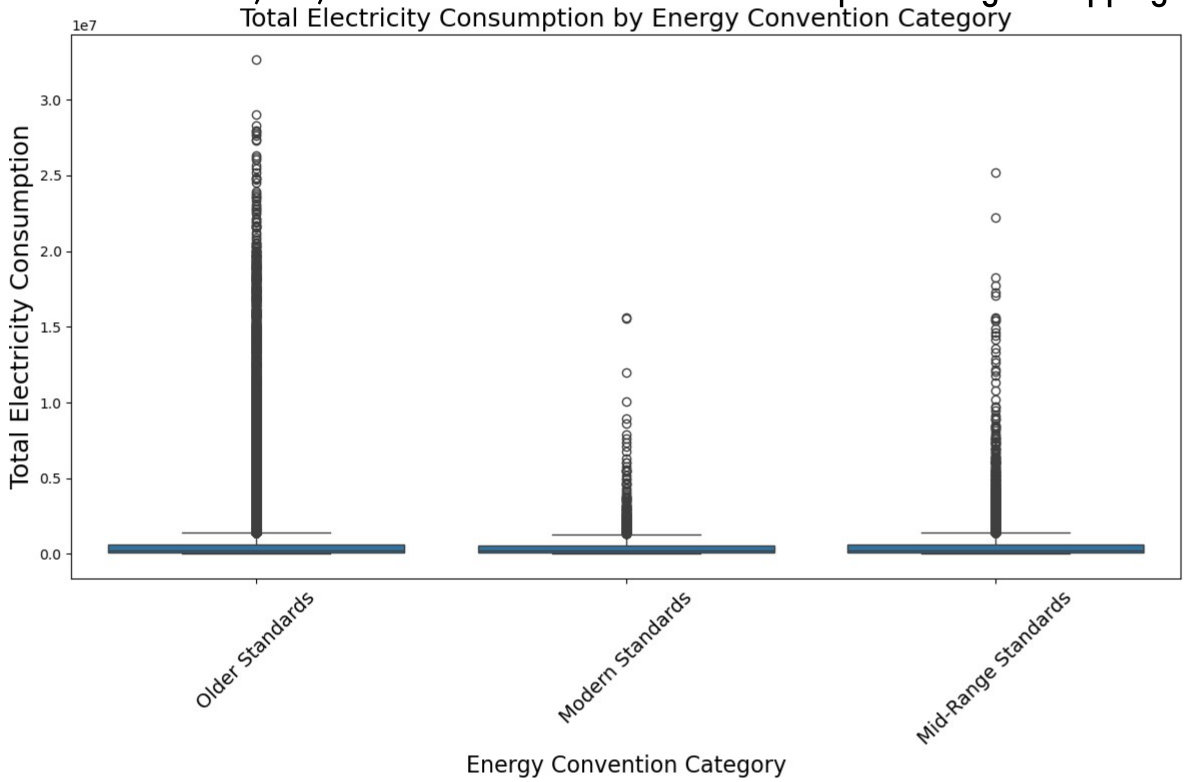

Figure A.3: *Total electricity consumption of all buildings, partitioned by each category of standards: the box plots are shown to assess the electricity consumption spread, highlighting the median, inter quartile range, and outliers for each group. Buildings with modern standards exhibits a more compact range of energy consumption, suggesting improved efficiency compared to older and mid-range standards.*

- MediumOffice, i.e., mid-sized office buildings, commonly used by businesses, law firms, or consultancies.
- QuickServiceRestaurant, i.e., fast-food facilities focused on high-speed service and limited on-site customers.
- FullServiceRestaurant, i.e., restaurants and related businesses offering service and an ex-ten-sive menu.
- SmallHotel, i.e., small-scale hotels with limited rooms and amenities.
- Hospital, i.e., large healthcare facilities providing inpatient and outpatient services,

emer-gency care, and specialized treatments.

- SmallOffice, i.e., small office buildings housing independent professionals or small businesses.

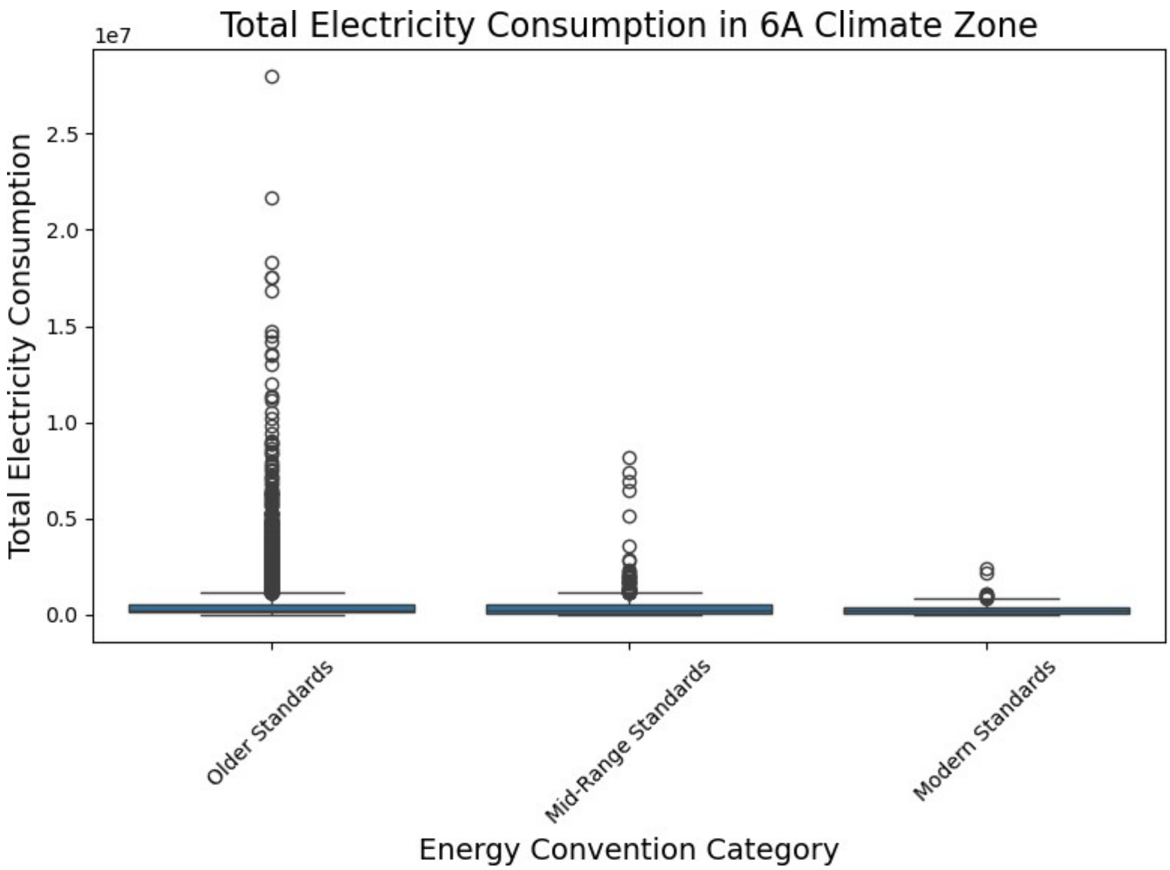

Figure A.4: *Different climate zone: Electricity usage of commercial buildings sectioned by standards in climate zone 6A*. This plot was made by ranging buildings based on their energy convention standards and showing there electricity consumption in every climate zone.

- Warehouse: Refers to buildings primarily used for storage and distribution of goods. Energy usage depends on heating, cooling (if climate-controlled), and lighting.

- LargeHotel, i.e., large-scale hotels offering extensive amenities such as conference rooms, restaurants, gyms, and spas.

- SecondarySchool, i.e., middle and high schools that provide education for teenagers, also hosting classrooms, laboratories, libraries, and sports facilities.

- RetailStripmall, i.e., clusters of retail stores that share a single building structure and park-ing area.

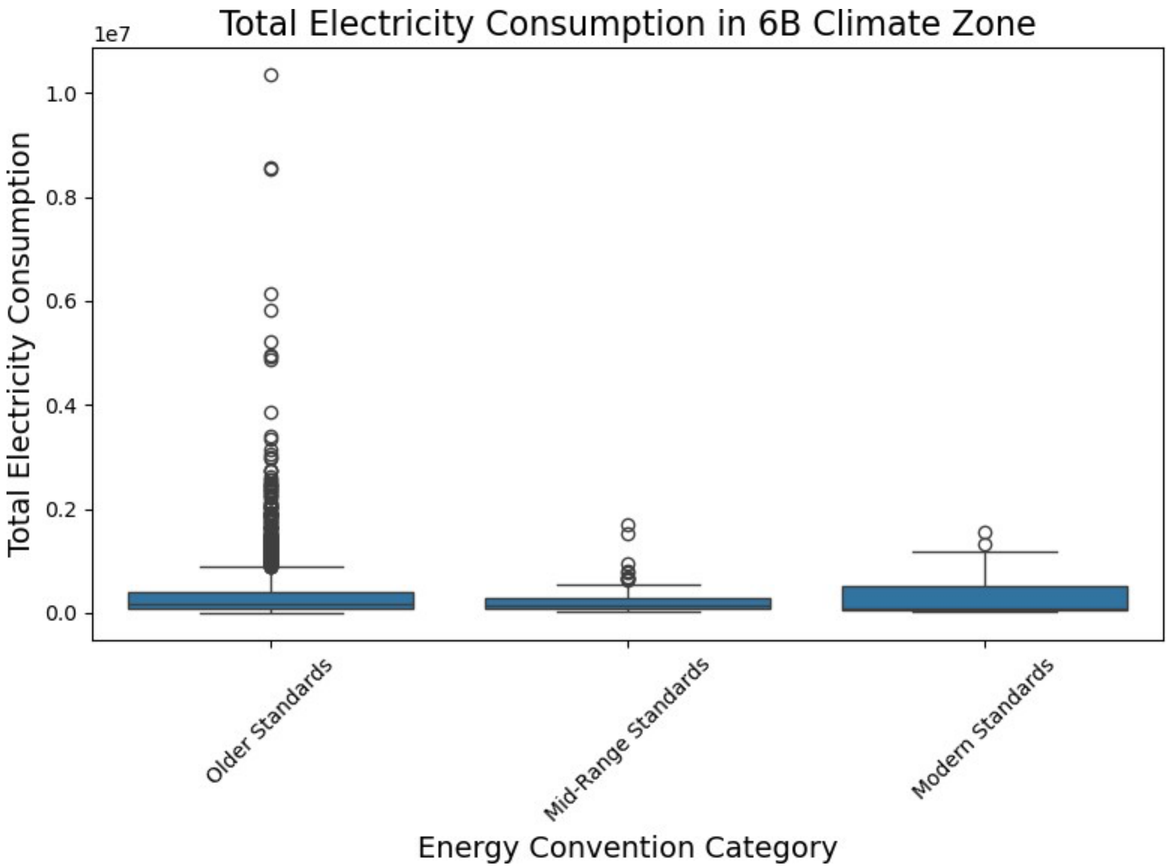

Figure A.5: *Different climate zone: Electricity usage of commercial buildings sectioned by standards in climate zone 6B*

For each building, we dispose of data about their square footage, energy usage conventions, and operational features such as: Square Feet (i.e., the total floor area of the building), Cooling Temperature Delta (i.e., the difference in cooling target temperature settings, measured in Fahren-heit degrees), the Heating Temperature Delta (as before but relative to heating), Number of floors in the building, Total Electricity Consumption of the building over a specified period, Total Site Energy Consumption, including all energy sources, Natural Gas Consumption, Cooling Energy (i.e., the energy consumed by cooling systems in the building), Eeating Energy (as before but rel-ative to heating), Interior Lighting Energy (i.e., the energy consumed by interior lighting systems within the building), Exterior Lighting Energy (i.e., the energy consumed by exterior lighting systems outside the building), Fans Energy (i.e., energy consumed by fans used in HVAC systems or other ventilation systems), Interior Equipment Energy (i.e., the energy consumed by inte-rior equipment such as appliances and office equipment), Refrigeration Energy, Water Systems Energy, Pumps Energy, Heat Recovery Energy (i.e., the energy consumed or saved by heat recovery systems in the building).

Similarly to what introduced on the main text, we have performed a correlation analysis amongst the different variables over all buildings, whose outcome is reported on the correlation matrix shown in figure B.6. As expected, we have found a strong positive correlations between **Total Electricity Consumption** and both the buildings' **Square Feet** (0.79) and **Total Site Energy Consumption** (0.73).

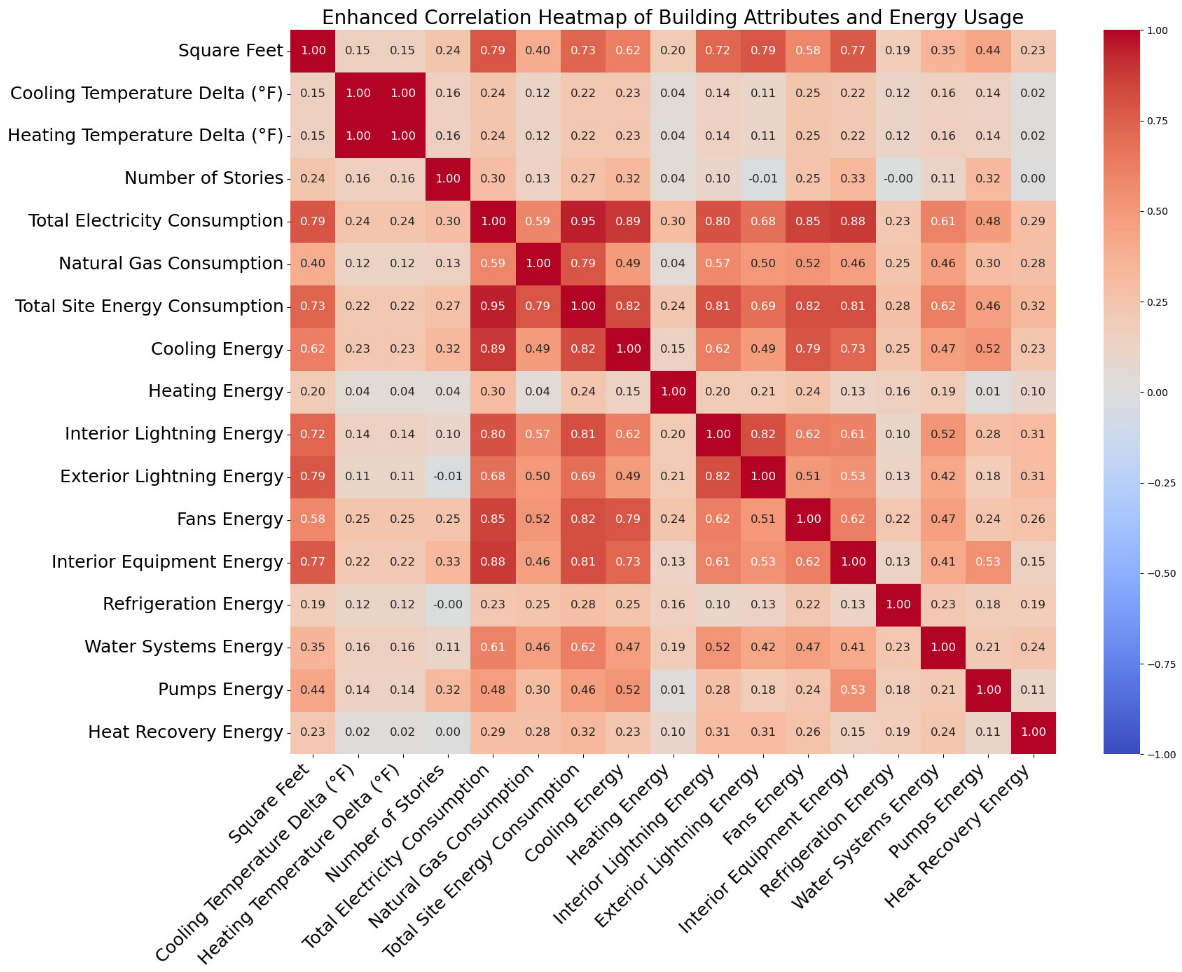

Figure B.6: Correlation matrix amongst all commercial buildings' operational features.

More interestingly, we remark a moderate correlation between **Natural Gas Consumption** and the building size (0.40), suggesting that larger buildings still rely on natural gas systems. We also remark that cooling systems and lighting highly contribute to larger buildings' overall energy demand, as witnessed by significant positive correlations between (**Cooling Energy – Interior Lighting Energy**) and (**Square Feet–Total Electricity Con-sumption**). Interestingly, Cooling and heating temperature deltas show low (albeit positive) correlations with **Total Electricity Consumption** and **Total Site Energy Consumption**, suggesting non-linear behaviours of these variables with respect to the energy consumption pat-terns: a further investigation of these aspects is left for further works.

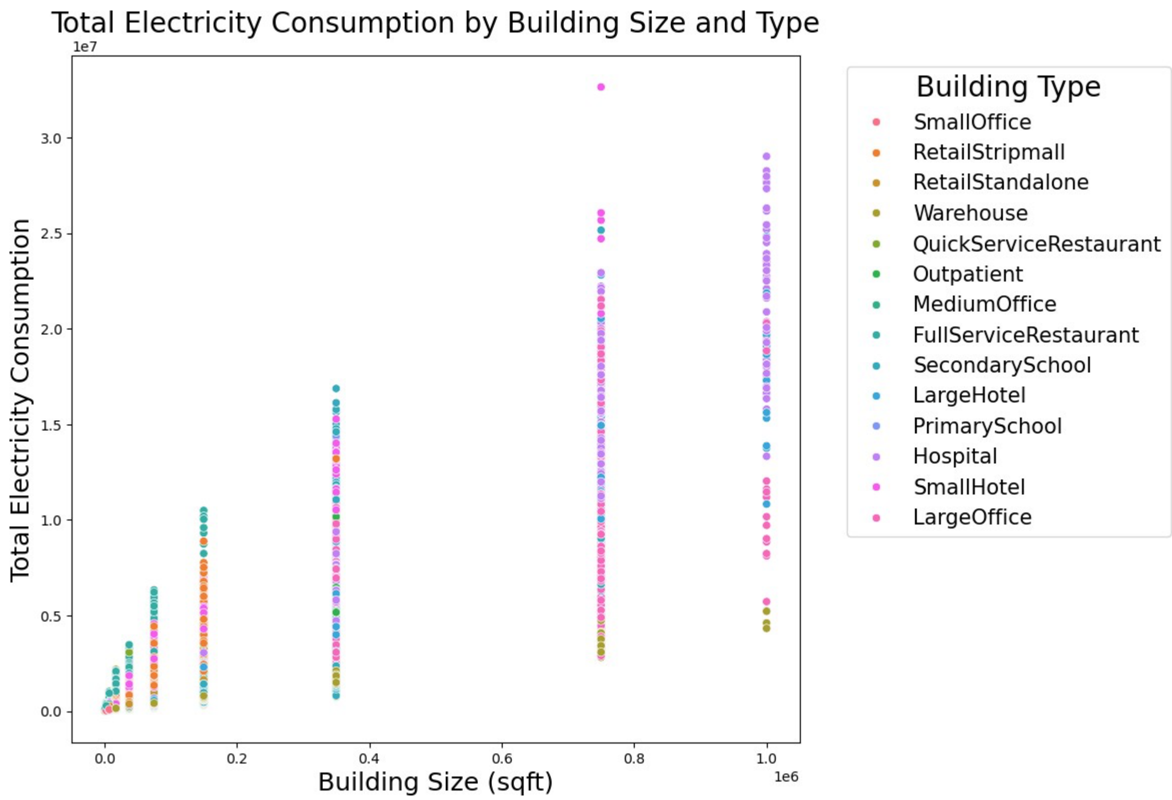

Figure B.7: *Electricity usage of commercial buildings with different sizes. The commercial buildings are partitioned in the building types shown in the legend.*

Furthermore, the **Fans Energy** (0.58) and **Interior Equipment Energy** (0.77) highlight a notable correlation to elec-tricity consumption, especially in larger buildings. As expected, we have found strong positive correlations between the building size and the energy usage (a linear regression between these two components would lead to an R^2 of 0.62). Figure B.7 shows the energy consumption of the buildings taken into account, that are partitioned in the building types shown in the legend. Overall, we may assert that Hospitals and Large Offices shows the biggest portion of energy consumption (see figure B.8), but, for ease of understanding, if we partition the buildings into **small-sized** (up to 200, 000 sqft), **medium-sized** (between 200, 000 sqft and 400, 000 sqft) and **large-sized** (above 600, 000 sqft), we remark that in the first class the highest energy consumption is mostly associated with full-service restaurants and medium offices, secondary schools and small hotels emerge as the primary contributors to energy consumption of the second class, whilst large offices and hospitals show the energy usage, with occasional contributions from large hotels.

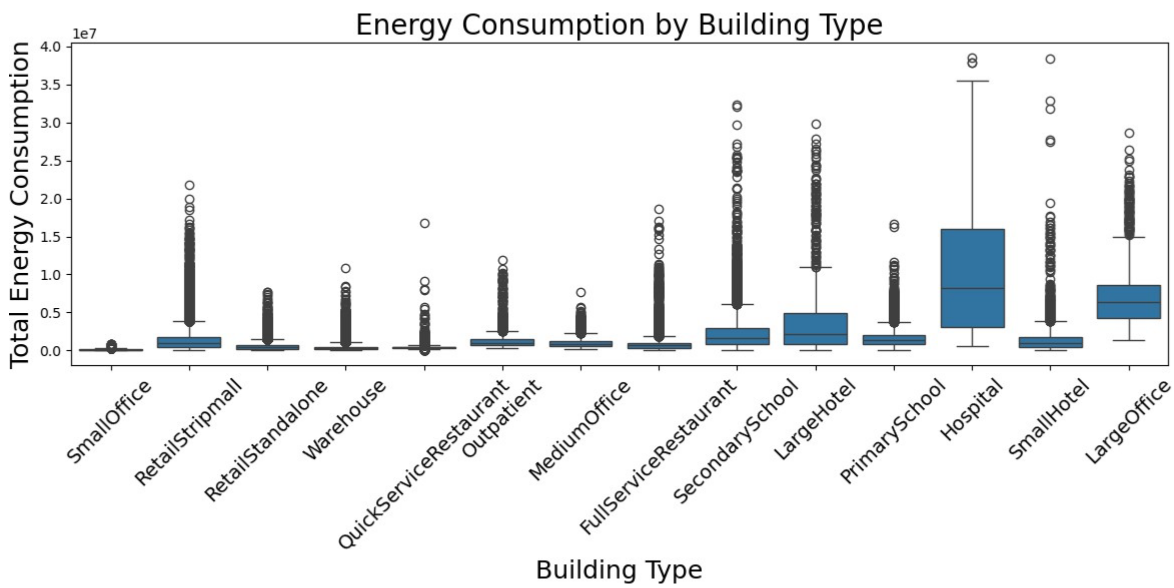

Figure B.8: *Electricity usage of commercial buildings partitioned by building type.* The plot was made by catego-rizing the buildings by their type and then creating a box plot for their energy usage.

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