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A Machine Learning-Based Framework for Predicting Place Attachment in Senior Housing: Toward Human-Centered and Age-Friendly Environmental Design

[1*] *Milad Olfat*
[1*] *Department of Art Education, Farhangian University, P.O. Box 14665-889, Tehran, Iran.*

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ABSTRACT: The psychological bond between elderly residents and their living environment—termed place attachment—plays a critical role in aging-in-place strategies. This study investigates the impact of environmental design characteristics on place attachment and evaluates the predictive capabilities of machine learning in this context. Methods: A cross-sectional survey was conducted among 490 elderly residents in Tehran using a 38-item Likert-scale questionnaire. The study applied three regression-based algorithms—Linear, Polynomial, and Ridge Regression—to model the relationship between 20 environmental design variables and place attachment scores.

"Positive Home Experiences" ($r = 0.68$), "Freedom from Confinement" ($r = 0.64$), and "Safety Features" ($r = 0.53$) emerged as the most influential predictors. Ridge Regression achieved the highest prediction accuracy, with an R^2 value of 0.6792.

The findings demonstrate the potential of machine learning to support human-centered design by enabling the early-stage evaluation of housing for the elderly. The proposed predictive framework can inform architecture curricula, computer-aided design (CAD) tools, and age-friendly housing policies.

Keywords: *Place Attachment, Environmental Design, Machine Learning, Elderly Housing, Ridge Regression, Human-Centered Design*

INTRODUCTION

The design of the built environment, encompassing urban planning and residential settings, plays a crucial role in enhancing the physical and mental health of elderly individuals. Factors such as urban spaces and adaptable housing designs are associated with improved well-being and social connections within this demographic (Gobbens & Van Assen, 2018; Feng et al., 2018). The concept of is a multifaceted psychological construct that influences feelings of security, comfort (Jain, 2023), identity, belonging (Perreault et al., 2020; Pohl et al., 2020), autonomy (Soleimani & Gharehbaglou, 2021), and social and cultural dimensions (Jain, 2023; Board & McCormack, 2018). It can be argued that physical environments alone do not fully determine the well-being and perceptions of the elderly; emotional and psychological factors also play a critical role in shaping personal well-being and perception. This dynamic becomes particularly evident in cases of migration, where individuals experience varying senses of identity and belonging as they transition between multiple homes (Sharifonnasabi et al., 2024; Foxwell et al., 2024). Furthermore, elderly residents in large cities, such as Tehran, face specific challenges related to their physical environment and housing. These challenges include the need for accessible housing (Ghaedrahmati & Shahsavari, 2019), ensuring physical and social sustainability (Sheikhazami & Aliakbari, 2020), promoting age-friendly urban design (Sharqi et al., 2016), and encouraging public participation in urban planning (Jelokhani-Niaraki et al., 2019). Given these considerations, the sense of home and the design of suitable environments and housing for the elderly are of paramount importance.

Research on the concept of home and the influence of environmental factors can be categorized into two main areas. The first category encompasses qualitative studies, many of which highlight the multidimensional nature of the sense of home, particularly within nursing homes and residential care facilities. For instance, some studies emphasize the significance of meaningful and personalized objects, which foster a sense of continuity with the past, as well as familiarity with the surrounding environment (Van Hoof et al., 2016; Annink & van Hees, 2022). Other critical factors identified include the

*Corresponding Author Email: *: M.olfat@cfu.ac.ir* *ORCID: 0000-0002-6772-3276*

design and control of living spaces (Matarese et al., 2022), autonomy and security, freedom from restrictions (Harris et al., 2020), and social participation, social connections, and a sense of belonging through shared spaces (Kuurne & Gómez, 2019; Ariyawansa et al., 2023). Positive relationships and moments of well-being are also recognized as essential components (Rinnan et al., 2018; Van Hoof et al., 2016).

Furthermore, some studies have employed photography to illustrate the importance of personal spaces and social activities (Van Hoof et al., 2015; Annink & van Hees, 2022). Research conducted in Italy has also identified meaningful relationships and a personalized environment as significant factors in shaping the sense of home among the elderly (Facchinetti et al., 2024). Overall, the findings from these studies underscore the importance of psychological, social, and environmental factors in the development of the sense of home.

The second category comprises quantitative studies, which, although limited in number, offer valuable insights. One study demonstrates that overcrowding and excessive density harm the space, identity, and satisfaction of residents (Perreault et al., 2020). Other research emphasizes the role of autonomy (Weber et al., 2024) and competition in shaping the sense of home (Soleimani & Gharehbaglou, 2021). These findings, in conjunction with qualitative research, underscore the complexity of the relationships between environmental, psychological (Gokce & Chen, 2020; Gharebaglou et al., 2021), social (Rijnaard et al., 2016), and health factors (Matarese et al., 2022). However, these studies have primarily concentrated on descriptive analyses and have seldom ventured into prediction or precise modeling using programming algorithms to explore the role of physical and environmental factors (Gu et al., 2021) in enhancing place attachment and the sense of home. There is an urgent need for a robust mathematical model to predict the sense of place attachment in the living environments of the elderly. Numerous studies have highlighted the significance of improving environmental design in early-stage evaluations, optimizing resource management, and enhancing the efficiency of monitoring processes through machine-learning algorithms (Feng et al., 2019; Aboagye et al., 2024; Kazeem et al., 2023; Santiago del Rey, 2024; Wilcox et al., 2013; Sun & Scanlon, 2019; Castellanos-Nieves & García-Forte, 2023; Gutiérrez et al., 2023; Hino et al., 2018; Sun et al., 2022).

Recent research has explored algorithmic approaches for predicting user behavior in spatial design. For instance, it has been demonstrated that generative design systems and various algorithms, such as EMFPCM, can enhance predictions of user behavior and create optimal spatial configurations (Vavilov et al., 2013; Shanthi & Suganya, 2013; Ji & Jun 2014; Derix, 2012). Liu et al. (2017) demonstrated that machine learning models can achieve moderate to high accuracy in estimating individuals' actual experiences within an environment. In the realm of psychological studies, Halde et al. (2016) investigated the impact of psychological factors on predicting individual performance using machine learning algorithms, including Neural Networks and Decision Trees. Their findings highlight the applicability of these algorithms in psychological contexts, suggesting their potential for predictions in interdisciplinary fields related to environmental psychology. Despite existing research, the application of machine learning algorithms to predict psychological variables—particularly the sense of home and place attachment—remains in its infancy, with limited studies examining these factors concerning the physical environment. Conversely, predicting human behavior in designed spaces through algorithms and machine learning can enhance user experiences across various domains. However, challenges such as privacy concerns and potential biases in algorithms (Atta-ur-Rahman et al., 2019) must be addressed in this context.

Moreover, no specific algorithm has been proposed for predicting the sense of home and quality of life-based on the environmental and demographic characteristics of the elderly. Data collection has primarily been conducted through observation or surveys (Matarese et al., 2022; Almevall, 2021; Board & McCormack, 2018; Rijnaard et al., 2016; Hale et al., 2019; Weil, 2019; Van Leeuwen et al., 2019; Guggemos et al., 2016). This research gap is particularly significant for the elderly living in large metropolitan areas such as Tehran, as studies indicate that this city requires improvements to become an age-friendly city (Nemati & Agha Bakhshi, 2013). Therefore, this research aims to address this gap by proposing an interdisciplinary model. Based on environmental psychology, studies suggest that the application of machine learning algorithms to predict psychological variables, particularly the sense of home and place attachment, is still in its nascent stages, with limited research conducted concerning the physical environment. Additionally, predicting individuals' behavior in designed spaces using algorithms and machine learning can enhance the experiences of others across various fields. However, challenges such as privacy concerns and the potential for algorithmic bias (Atta-Ur-Rahman et al., 2019) must be carefully considered.

This research aims to identify the environmental characteristics that influence the perception of a sense of home. In the second phase, the focus shifts to predicting place attachment among the elderly using machine learning algorithms, with the intention of assessing the role of environmental features in the precise evaluation of the primary objective: place attachment. In this phase, machine learning techniques such as Polynomial Regression, Linear Regression, and Ridge Regression are employed for prediction. This research seeks to integrate the fields of environmental design and machine learning to enhance the quality of life for the elderly and is guided by the following questions:

-What physical environmental factors related to the perception of home influence place attachment in the elderly?

-How can machine learning algorithms be utilized to predict place attachment among the elderly in their current housing situations?

-What is the accuracy of machine learning algorithms in predicting the final target of place attachment?

Continuing this research, the first section will focus on examining the environmental factors that influence the perception of a sense of home in elderly housing, along with a review of the related literature. The second phase will discuss the research methodology and the criteria for selecting the algorithms. The third section will present the quantitative results, including the accuracy of the algorithms and the correlation between variables. Finally, the fourth section will provide an interpretation of the research findings in a practical context, addressing the research questions and concluding the study.

Literature Review on Environmental Factors Influencing the Development of a Sense of Home in the Elderly

A high-quality physical environment in care and residential settings is essential for the well-being of the elderly. Creating a home-like atmosphere through aesthetic elements and opportunities for meaningful activities enhances feelings of security and fosters social connections among older adults (Dahlan et al., 2016; Ottoni et al., 2016). Additionally, small-scale units are particularly beneficial for individuals with disabilities and those who have dementia (Joseph et al., 2015). Access to outdoor spaces for physical activities and interaction with nature is also deemed essential (Bengtsson et al., 2015). Designs that promote place attachment and facilitate social interactions also contribute to the well-being and health of the elderly (Friesen et al., 2016).

Furthermore, addressing residents' needs by providing natural light, comfortable furniture, and various amenities enhances their sense of comfort and overall well-being. Involving residents in the design process ensures that their preferences are considered, thereby increasing satisfaction and fostering a sense of belonging. Therefore, the role of the environment in enhancing place attachment and the perception of home among the elderly is undeniable. The following factors are categorized and summarized based on the research literature:

Personalization and Physical Design: The physical arrangement and personalization of spaces are crucial for cultivating a sense of home among elderly residents. Features such as small-scale designs, comfortable furniture, and natural materials—such as wooden outdoor elements and decorative plants—significantly influence this environment (Lundgren, 2000; Oswald et al., 2006, 2007). Flexibility in interior layouts enables residents to incorporate personal items and tailor their surroundings to their preferences, thereby fostering a sense of familiarity and ownership (Van Hoof et al., 2016; Annink & van Hees, 2022). Furthermore, lighting that simulates natural conditions and access to outdoor spaces, such as gardens or balconies, enhances the comfort and well-being of elderly individuals (Fleming et al., 2015; Eijkelenboom et al., 2017).

Integration of Private and Public Spaces: Effective architectural design arises from the harmonious integration of public and private spaces. Public areas serve to separate quiet bedrooms or workspaces from dining areas, thereby enhancing social interactions and alleviating feelings of isolation among residents (Robinson et al., 2010; Hauge & Kristin, 2008; O'Neill et al., 2022). Additionally, accessibility features such as wheelchair-friendly pathways and proximity to essential services significantly contribute to the independence of residents (Ariyawansa et al., 2023; Van Hoof et al., 2016; Shield et al., 2014).

Cultural and Contextual Advancements: The integration of cultural and natural elements has a significant influence on creating a sense of home. Artificial decorations that reflect local customs, along with the incorporation of natural light and plants into interior spaces, foster a strong emotional connection with the environment (Liu & Gallois, 2022; Gharebaglou et al., 2021). Public spaces equipped with benches, recreational facilities, and thoughtful landscaping contribute to the establishment of social connections and a sense of place (Boccagni & Duyvendak, 2021; Faulkner, 2023; Tang et al., 2022).

Therefore, after reviewing the existing literature, several essential characteristics for perceiving the sense of home through architectural design have been identified and organized in Table 1. These findings provide a scientific foundation for creating environments that not only meet functional needs but also enhance emotional satisfaction and foster a strong sense of belonging for the elderly. These elements serve as the primary basis for identifying the relationships between environmental factors and place attachment among the elderly, which are utilized in this research.

Table 1: Environmental Factors Extracted in the Formation of the Meaning of Home from the Literature Review.

Feature	Details	References
Private bedrooms with dedicated bathrooms	Enhance privacy and functionality to accom-.modate personal needs effectively	Robinson et al., 2010
Recreational and community facilities	Access to gyms, cinemas, pools, libraries, laundry, workshops, and psychological counseling centers	Ariyawansa et al., 2023; Van Hoof et al., 2016
Safety features	Non-slip floors, guarded outlets, secure windows and balconies	Shield et al., 2014; Harris et al., 2020
Functional living spaces	Ensure activities and daily requirements are fulfilled comfortably	Oswald & Kaspar, 2012
Comfortable furniture and decorations	Visually attractive and emotionally comforting environment	Lundgren, 2010; Liu & Gallois, 2021
Freedom from confinement	Thoughtful spatial planning avoids feelings of restriction	Oswald & Kaspar, 2012
Accessibility	Easy access to bathrooms, living rooms, and outdoor areas	Van Hoof et al., 2015; Eijkelenboom et al., 2017
Flexible décor	Residents can modify room design and decorations	Annink & van Hees, 2023; Tang et al., 2022

Continiue of Table 1: Environmental Factors Extracted in the Formation of the Meaning of Home from the Literature Review.

Feature	Details	References
Green spaces and nature views	Provide a restorative connection to the environment	Fleming et al., 2015; Faulkner, 2023
Safe pathways	Wheelchair-friendly ramps, stairs, and elevators	Van Hoof et al., 2016; Eijkelenboom et al., 2017
Integration of private and communal spaces	Encourages social interactions while maintaining privacy	Robinson et al., 2010
Optimal comfort	Heating, cooling, lighting, and sound insulation	Oswald et al., 2007; Gharebaglou et al., 2021
Positive home experiences	Enhance emotional satisfaction and attach-.ment	Oswald & Kaspar, 2012; O'Neill et al., 2020
Adequate bedroom size	Accommodates furniture, photos, and unique possessions	Robinson et al., 2010
Nature indoors and outdoors	Potted plants, natural light, fresh air, and landscaped outdoor spaces	Fleming et al., 2015; Liu & Gallois, 2021
Public areas for diverse activities	Family dining spaces, conversation zones, and walking paths	Robinson et al., 2010; Boccagni & Duyvendak, 2021
Connection to natural surroundings	Seamless integration with open spaces and greenery	Eijkelenboom et al., 2017; Faulkner, 2023
Easy navigation	Accessible pathways within rooms ensure smooth movement	Van Hoof et al., 2015; Eijkelenboom et al., 2017
Cleanliness and aesthetics	Visually appealing, odor-free, and clean spaces	Harris et al., 2020; Gharebaglou et al., 2021
Daylight access	Bright and cheerful atmosphere through natural lighting	Fleming et al., 2015; Oswald et al., 2007

MATERIALS AND METHOD

Procedures and Participants

This cross-sectional study was conducted using a researcher-developed questionnaire distributed on social media platforms. Participants were invited to complete an online survey on the website https://porsall.com/. Data were collected from December 22, 2023, to March 19, 2024. A total of 490 individuals provided their consent to participate, and only participants from the 22 districts of Tehran (N = 490) were included in this study. Detailed demographic information about the study sample is presented in Table 2.

Environmental and Physical Factors

Key dimensions of the environmental characteristics of the sense of home were assessed using data obtained from a literature review and organized into a researcher-developed questionnaire. It is important to note that this questionnaire had previously been evaluated and refined for content validity by 25 experts, with the Content Validity Ratio (CVR) calculated (Oswald et al., 2007; Fleming et al., 2015; Oswald & Kaspar, 2012; Van Hoof et al., 2015; Eijkelenboom et al., 2017; Robinson et al., 2010; Harris et al., 2020; O'Neill et al., 2020; Gharebaglou et al., 2021; Liu & Gallois, 2021; Boccagni & Duyvendak, 2021; Faulkner, 2023). This questionnaire consists of 20 items designed to assess respondents' affinity for the physical environment of their homes and the extent of their sense of belonging within them. Respondents rated each item on a 5-point Likert scale, ranging from 1 (very little) to 7 (very much). The questionnaire is based on the one developed by Oswald et al. (2010), which associates the sense of home with physical bonding, behavioral bonding, cognitive/emotional bonding, and social bonding (Oswald et al., 1999; Oswald et al., 2006). The internal consistency, as indicated by Cronbach's alpha ($\alpha = 0.93$), and the construct validity indices of model fit—namely, the Normed Fit Index (NFI = 0.93), Standardized Root Mean Square Residual (SRMR = 0.066), R-squared ($R^2 = 0.56$), and Q-squared ($Q^2 = 0.43$)—along with factor loadings ($\lambda > 0.4$), were deemed acceptable.

Outcome Variable

Place Attachment

Place attachment was assessed using the subscales of the Measurement of Place Attachment questionnaire developed by Williams and Vaske (2003). This quick and straightforward screening tool evaluates the emotional and symbolic connections between individuals and specific locations. The questionnaire comprises 12 items designed to provide a valid and reliable means of understanding how individuals value and emotionally connect with a place, thereby facilitating informed decision-making (Williams & Vaske, 2003). It measures two key dimensions of place attachment: place dependence and place identity.

The questionnaire employs a 5-point Likert scale for scoring. Participants are asked to evaluate their attachment to their current housing on a scale ranging from "strongly disagree" (0) to "strongly agree" (4). The scores for these items are aggregated to compute the overall place attachment score. To determine the total score, the sum

Table 2: Demographic characteristics of the sample (N = 490).

Variable	N %
Age	
65-74	236 (48.2)
75-84	158 (32.2)
and above 85	96 (19.6)
Gender	
Male	244 (49.8)
Female	246 (50.2)
Living situation	
Alone	172 (35.1)
With family or friends	318 (64.9)
Physical condition	
Healthy	311 (63.5)
Needs assistive devices	179 (36.5)
Housing status	
Owner-occupied	292 (59.6)
Rented	198 (40.4)
Duration of residence	
to 10 years 1	186 (38)
to 30 years 11	200 (40.8)
More than 31 years	104 (21.2)

of the scores for each question is calculated. The score range will be between 12 and 60, with higher scores indicating a stronger attachment to the place and lower scores reflecting the opposite (Williams & Vaske, 2003).

This questionnaire has been extensively utilized in environmental psychology to evaluate the emotional and functional values of recreational sites, inform land-use planning, and explore cultural and personal connections to places. This is why it was employed in the current study (Brown & Raymond, 2007). The tool has been validated in several studies, including those involving students from Colorado State University (65 participants), the University of Illinois (380 participants), visitors to Shenandoah National Park (2,005 participants), and the Mt. Rogers National Recreation Area (369 participants). In these studies, confirmatory factor analysis validated the two-dimensional structure of place attachment, distinguishing between place dependence and place identity. Furthermore, convergent validity was established through the correlation of questionnaire scores with behavioral and psychological variables related to place attachment, such as visitation frequency and emotional connections (Williams & Vaske, 2003). In the current study, the Cronbach's alpha coefficient for the overall place attachment score was 0.93.

Machine Learning Algorithms

The machine learning model was developed by inputting the dataset obtained from the completed questionnaire gathered in the previous stage. The model was implemented using the Python programming language within the Anaconda software and the Jupyter Notebook environment, version 7.0.8. The primary specifications of the development environment included a 2.40 GHz Intel Core i7 processor, an integrated Intel® HD Graphics 4000 processor with 32 MB of graphics memory (VRAM), and 8 GB of RAM. The development utilized several packages, including NumPy, pandas, Matplotlib, and Scikit-learn. Additionally, the preprocessing module from Scikit-learn, which facilitates the conversion of raw datasets into an appropriate format, was employed to standardize the data efficiently (Sari et al., 2022; Carneiro et al., 2018).

The environmental factors assessed in this study consist of 20 items derived from previous research that measure the sense of home in older adults. These factors include private bedrooms with en-suite bathrooms, recreational and social facilities, safety features, functional living spaces, comfortable furniture and decorations, freedom from constraints, accessibility, flexible décor, green spaces and natural views, safe pathways, integration of private and public spaces, optimal comfort, positive home environment experiences, appropriately sized bedrooms, the presence of nature both indoors and outdoors, public spaces for diverse activities, connection to the natural environment, ease of navigation, cleanliness, aesthetics, and access to natural light. Each factor is rated on a Likert scale ranging from 0 (very little) to

4 (very much). These items are considered features for predicting the dependent variable, namely place attachment (measured with 12 items), which serves as the primary target for assessing the level of place attachment in older adults residing in residential houses in Tehran. The goal is to achieve an appropriate level of accuracy using either linear or nonlinear machine learning models. The research process is illustrated in Fig. 1.

RESULTS AND DISCUSSION

Machine Learning Process

In this study, a total of 490 data points concerning the housing of elderly residents in Tehran were collected and utilized as training and testing datasets, with 392 data points allocated for training (80%) and 98 data points for testing (20%). The generated datasets were imported into Jupyter Notebook and processed using Linear Regression, Polynomial Regression, and Ridge Regression algorithms, as illustrated in Fig. 3. The applications of these algorithms extend across various fields, including economics, social sciences, medicine, and engineering. Regression algorithms are primarily employed to model relationships between variables, analyze the effects of independent variables, and predict continuous values (James et al., 2013; Hastie et al., 2009). Given that the target data in this study were continuous, these algorithms were well-suited for data analysis. The textual data were initially converted into numerical format for improved readability and processing. During the feature extraction process, demographic information related to the elderly was transformed into numerical data,

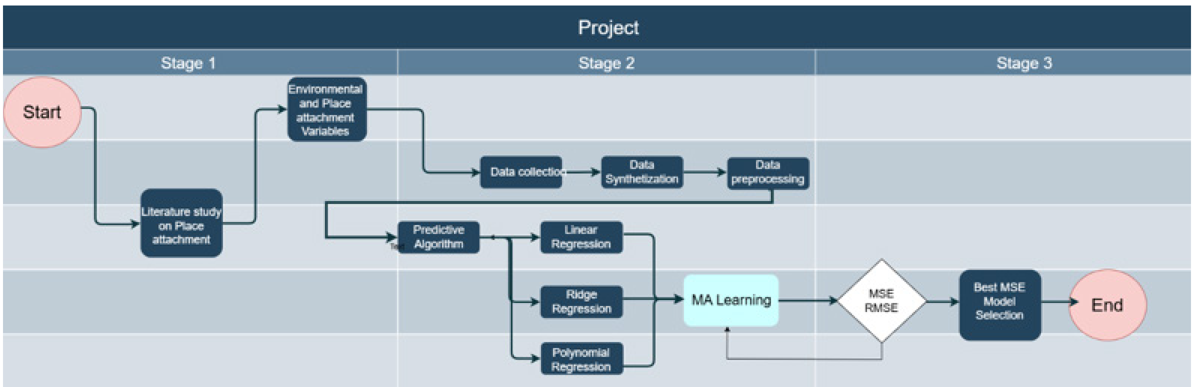

Fig. 1: Research workflow.

```
[1]: import pandas as pd
     data = pd.read_csv(r"C:\Drive D\ML article\Describe.csv")
     data
```

[1]:

	Age	Gender	Living situation	physical condition	Housing status	Duration of residence	q1	q2	q3	q4	...	q12	q13	q14	q15	q16	q17	q18	q19	q20	Place attachment
0	0.0	1	1	0	0	1	5	4	5	5	...	3	4	5	3	4	4	3	4	3	4.416667
1	0.0	0	1	0	1	0	5	5	5	5	...	5	4	5	4	5	4	4	4	3	4.416667
2	0.0	1	1	1	0	0	5	5	4	5	...	5	3	5	5	4	5	4	3	5	3.750000
3	0.0	0	1	1	1	0	1	4	1	3	...	3	2	1	2	1	3	3	3	4	1.666667
4	0.0	1	1	0	1	0	2	1	2	4	...	3	3	2	3	1	3	4	4	5	3.083333
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
485	2.0	0	0	1	0	2	5	5	5	4	...	5	5	5	4	4	4	5	5	5	4.500000
486	0.0	1	1	0	0	0	4	4	4	3	...	4	4	4	4	4	4	4	4	4	4.333333
487	0.0	0	1	0	1	1	4	4	4	4	...	4	5	4	5	5	5	4	3	3	4.416667
488	1.0	1	1	0	0	2	4	4	3	4	...	4	4	5	4	4	4	4	4	4	4.833333
489	0.0	0	1	0	0	2	1	3	4	4	...	3	4	2	4	4	4	4	4	4	4.500000

490 rows × 27 columns

Fig. 2: Data Input Process.

with the value (0) assigned to private housing and (1) to rental housing. Other textual information, such as gender, age range, and physical condition, was also encoded similarly.

Descriptive and Inferential Data Analysis

In this section of the study, a Python algorithm was used to represent the summary statistics of the data visually. First, descriptive statistics were calculated using the `describe()` function from the pandas library, which included the mean, standard deviation, median, and the count of data points. Subsequently, leveraging the styling capabilities of pandas, these values were highlighted with a color gradient using the YlOrRd color map (yellow-orange-red) to distinguish patterns and variations in the data visually.

Based on the descriptive statistics provided, the average scores for most environmental components fall within the range of 3 to 4 (on a scale of 1 to 5), indicating a relatively high level of satisfaction among residents regarding these aspects. Specifically, features such as "Comfortable furniture and decorations" (mean score of 4.03) and "Optimal comfort" (mean score of 4.07) received the highest ratings, while "Safety features" (mean score of 3.00) and "Private bedrooms with dedicated bathrooms" (mean score of 3.20) received the lowest ratings. The standard deviation (std) also indicates a relatively balanced dispersion of the data, with most values ranging from 0.86 to 1.45. These results suggest that, although certain aspects such as "Cleanliness and aesthetics" are generally affirmed by the residents, improvements in areas like "Safety" and "Accessibility" could enhance overall resident satisfaction. These findings can serve as a foundation for designing and improving residential environments for elderly individuals in Tehran.

Furthermore, this study employed an algorithm utilizing the Matplotlib and Seaborn libraries in Python to visualize the correlation matrix between environmental variables and place attachment. The correlation matrix is a powerful tool in data analysis, as it displays the linear relationships between variables and helps identify patterns and dependencies within the data. In this algorithm, the correlation matrix was graphically represented using the heatmap function from Seaborn. This approach not only facilitates a quicker and more visual understanding of the relationships between variables but also serves as an effective means of presenting statistical analysis results in scientific research. This method enables researchers to interpret and analyze data with greater accuracy and to present their findings in a graphical and comprehensible format.

The correlation matrix in Fig. 4 illustrates the linear relationships between variables, with correlation values ranging from -1 to +1.

	count	mean	std	min	25%	50%	75%	max
Private bedrooms with dedicated bathrooms	490.000000	3.202041	1.454840	1.000000	2.000000	4.000000	4.000000	5.000000
Recreational and community facilities	490.000000	3.620408	1.164748	1.000000	3.000000	4.000000	4.000000	5.000000
Safety features	490.000000	3.002041	1.446382	1.000000	2.000000	3.000000	4.000000	5.000000
Functional living spaces	490.000000	3.889796	0.865197	1.000000	3.000000	4.000000	5.000000	5.000000
Comfortable furniture and decorations	490.000000	4.034694	0.853730	2.000000	4.000000	4.000000	5.000000	5.000000
Freedom from confinement	490.000000	3.751020	1.067865	1.000000	3.000000	4.000000	5.000000	5.000000
Accessibility	490.000000	3.879592	0.939799	1.000000	3.000000	4.000000	5.000000	5.000000
Flexible décor	490.000000	3.897959	0.958119	1.000000	3.000000	4.000000	5.000000	5.000000
Green spaces and nature views	490.000000	3.863265	1.017072	1.000000	3.000000	4.000000	5.000000	5.000000
Safe pathways	490.000000	3.259184	1.386529	1.000000	2.000000	4.000000	4.000000	5.000000
Integration of private and communal spaces	490.000000	3.938776	0.911372	1.000000	3.000000	4.000000	5.000000	5.000000
Optimal comfort	490.000000	4.069388	0.867077	1.000000	4.000000	4.000000	5.000000	5.000000
Positive home experiences	490.000000	3.855102	0.907492	1.000000	3.000000	4.000000	4.000000	5.000000
Adequate bedroom size	490.000000	3.667347	1.142932	1.000000	3.000000	4.000000	5.000000	5.000000
Nature indoors and outdoors	490.000000	3.804082	0.945544	1.000000	3.000000	4.000000	5.000000	5.000000
Public areas for diverse activities	490.000000	3.681633	1.093142	1.000000	3.000000	4.000000	4.000000	5.000000
Connection to natural surroundings	490.000000	3.775510	1.006427	1.000000	3.000000	4.000000	5.000000	5.000000
Easy navigation	490.000000	3.881633	0.873531	1.000000	3.000000	4.000000	4.000000	5.000000
Cleanliness and aesthetics	490.000000	4.010204	0.844747	1.000000	4.000000	4.000000	5.000000	5.000000
Daylight access	490.000000	3.844898	0.940143	1.000000	3.000000	4.000000	5.000000	5.000000
Place attachment	490.000000	3.856973	0.774156	1.166667	3.500000	4.083333	4.416667	4.916667

Fig. 3: Descriptive statistics for the mean, standard deviation, and median of environmental components influencing place attachment.

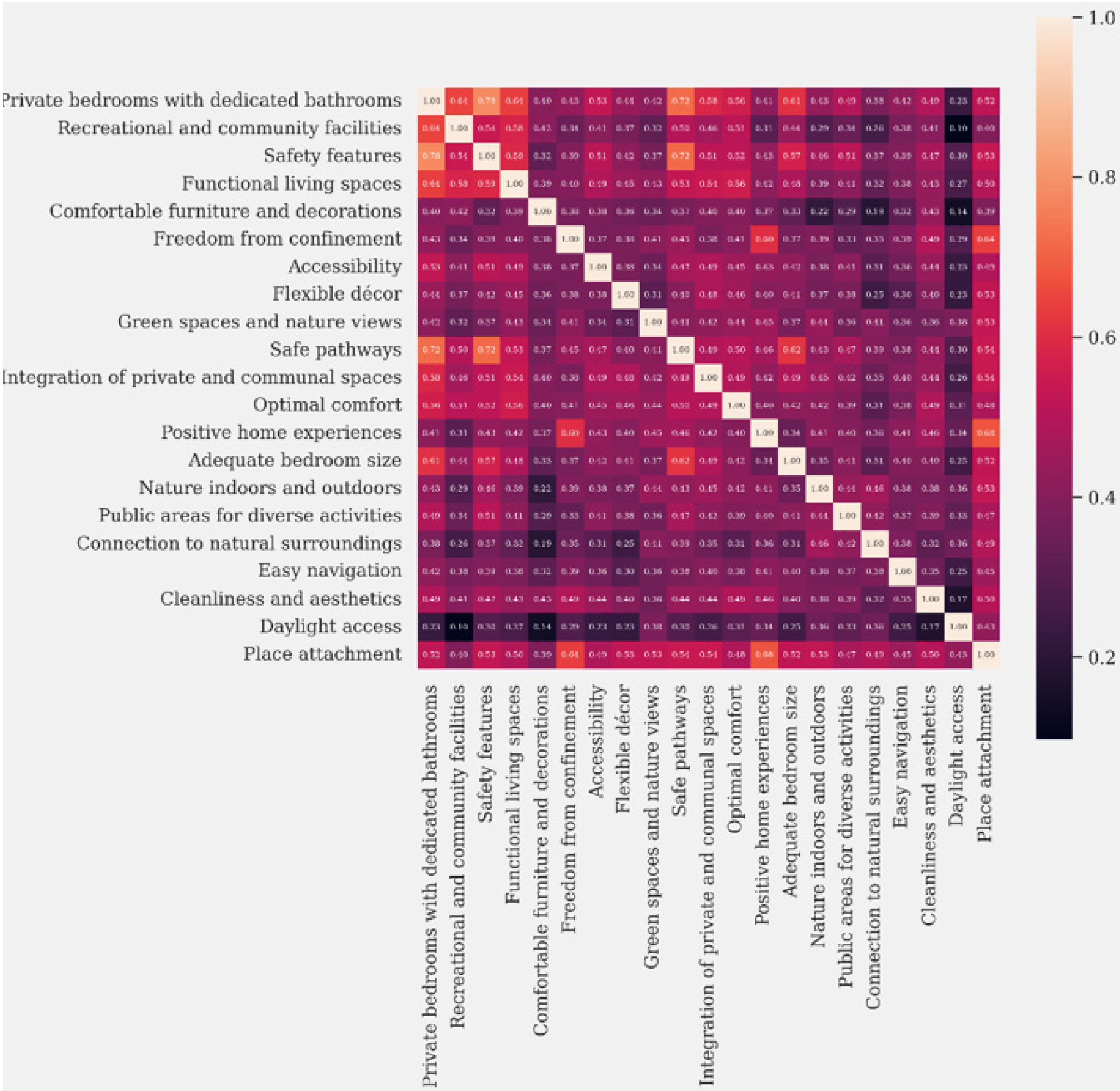

Fig. 4: Correlation between environmental variables and place attachment.

Generally, stronger positive correlations (close to +1) indicate a direct and meaningful relationship between variables, while correlations close to zero suggest a lack of significant association. The results revealed that some variables exhibited stronger correlations with one another. For instance, "Private bedrooms with dedicated bathrooms" demonstrated a strong correlation with "Safety features" (correlation of 0.78) and "Safe pathways" (correlation of 0.72). Additionally, "Positive home experiences" were highly correlated with "Freedom from confinement" (correlation of 0.60) and "Place attachment" (correlation of 0.68). Conversely, some variables, such as "Daylight access," displayed weaker correlations with other variables (e.g., a correlation of 0.10 with "Recreational and community facilities"). These findings suggest that enhancing certain features, such as safety and freedom from confinement, can positively impact residents' overall satisfaction and their attachment to the residential environment.

Additionally, "Positive home experiences" (0.68) and "Freedom from confinement" (0.64) have the most significant impact on "Place attachment." This suggests that satisfaction and freedom within the residential environment are key factors in fostering a strong attachment to a place. Furthermore, "Daylight access" (0.43) and "Recreational and community facilities" (0.40) exert the least influence on place attachment. This indicates that, while these factors are important, their impact is comparatively less significant than that of other elements.

Evaluation and Comparison of the Performance of Linear Regression, Polynomial, and Ridge Algorithms in Predicting Place Attachment

This section compares the performance of three algorithms — Linear

Regression, Polynomial Regression, and Ridge Regression — in predicting place attachment. As previously mentioned, environmental design factors related to the sense of home among elderly individuals play a significant role in shaping place attachment (Kermani & Paydar, 2024; Feng et al., 2022; Arghiani & Mirhashemi, 2021). In this section, we will examine the performance of these algorithms in predicting place attachment and evaluate their accuracy.

Evaluation of Algorithm Performance

Evaluation Criteria

In this study, data from the Training Set (80%) and Test Set (20%) were used to evaluate the model's performance and ensure its ability to generalize to new data. The training data is used to train the model and learn patterns, while the test data is employed to evaluate the model's performance on unseen data. This division also helps prevent overfitting, which occurs when the model becomes excessively fine-tuned to the training data and performs poorly on new data (Hastie et al., 2009). Additionally, the test data helps assess the model's generalization ability, that is, its capacity to make accurate predictions on new data (Bishop, 2006). This process plays a crucial role in selecting the optimal model and validating it (James et al., 2013). In general, using Train and Test data is a standard approach to ensure the performance and reliability of machine learning models. Moreover, the accuracy of both the Test and Train sets is measured, and the coefficient of determination (R^2) is used to assess the quality of the employed model.

Results of the Linear Regression Algorithm

In this study, linear regression was used to predict the target variable (Y), i.e., place attachment, based on a set of features. The model's coefficients revealed that some features had a greater impact on prediction. Specifically, the feature "Positive home experiences," with a weight of 0.207, showed the greatest influence. These coefficients indicate the importance of each feature in the model, helping better understand the relationship between the independent and dependent variables. The model coefficients, representing the significance of each feature in the prediction, were calculated as follows:

```
Model Coefficients (Weights):
 [[ 0.          -0.01052153   -0.02012634   0.02855438
0.02285543   0.0418191
     0.17549219    0.01957185    0.11676551    0.03243087
0.00338353    0.05225362
    -0.01127058    0.20745067    0.08162072    0.04633004
0.01787478    0.07833736
     0.00963853    0.00229832    0.03834556]]
------------------------------------------------
Model Accuracy on Test Data: 63.51096069529276%
R2 Score on Test Data: 63.51%
------------------------------------------------
Model Accuracy (Manual Calculation): 63.51%
```

This model was evaluated with an accuracy of 63.51% and a coefficient of determination (R^2) of 63.51%, indicating that the model was able to explain a significant portion of the variance in the target variable. Additionally, the model's accuracy was manually calculated, yielding the same result of 63.51%, confirming the findings. This accuracy suggests that the model performs reasonably well, but there is still room for improvement.

Ultimately, the results indicate that linear regression is an effective method for predicting the target variable in this study. However, to improve the model's accuracy, more advanced methods could be employed, alongside improvements in data preprocessing and the

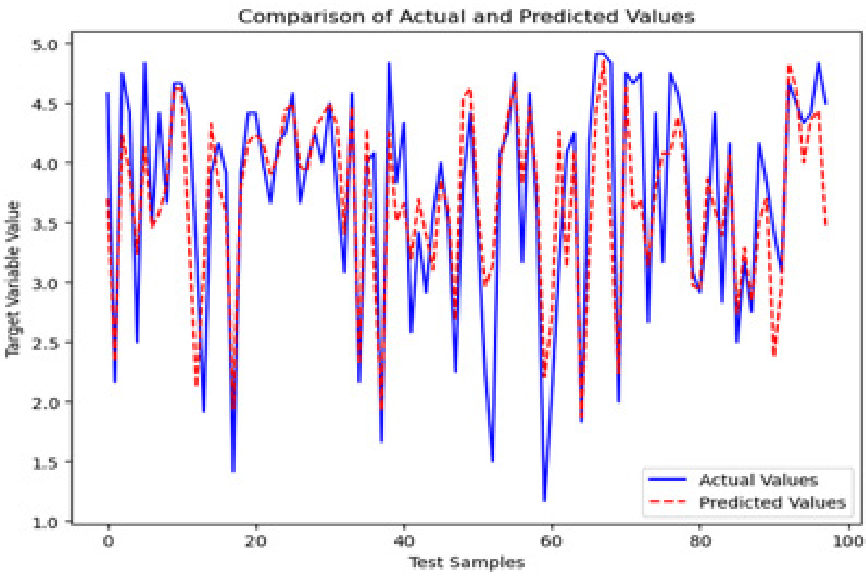

Fig. 5: Comparison of actual and predicted values.

selection of more relevant features. The following line chart (Fig. 5) compares the actual values (y_test) and the model's predictions (y_predict). The blue line represents the actual values, while the red line represents the predictions.

Additionally, the histogram chart (Fig. 6) illustrates the distribution of prediction errors (the difference between actual values and predictions), which helps in examining the distribution of errors and the performance of the model.

In the next step, to enhance the model's accuracy, the data are first divided into `train` and `test` sets and normalized using the MaxAbsScaler method to ensure the feature values fall within an appropriate range. The linear regression model is trained on the `train` data and then applied to the `test` data. The evaluation results show that the Mean Squared Error (MSE) is 0.2259, and the R^2 coefficient is 0.6777. The value of 0.2259 indicates that the average squared prediction errors are relatively low, and the closer this value is to zero, the higher the accuracy of the model's predictions. Additionally, the model explains approximately 67.77% of the variance in the target variable, demonstrating relatively good performance and an improvement in accuracy compared to its previous state. The Actual vs. Predicted plot also shows the relationship between the actual and predicted values, with a fairly good alignment observed between them

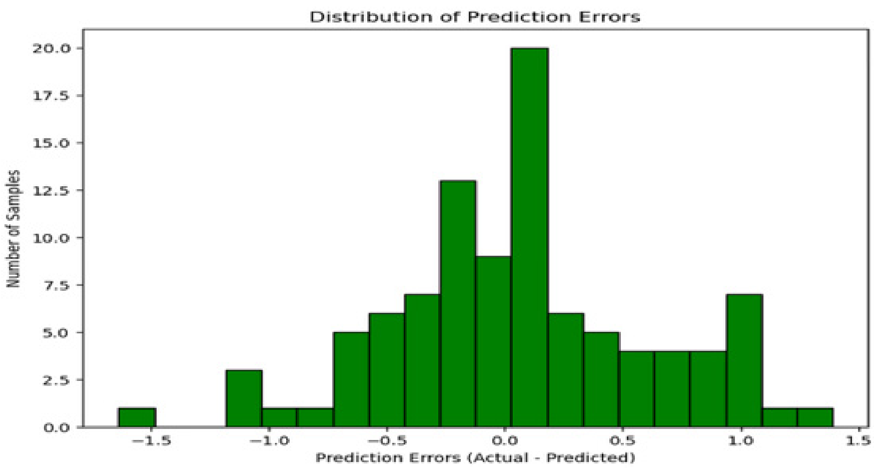

Fig. 6: Distribution of actual and predicted values

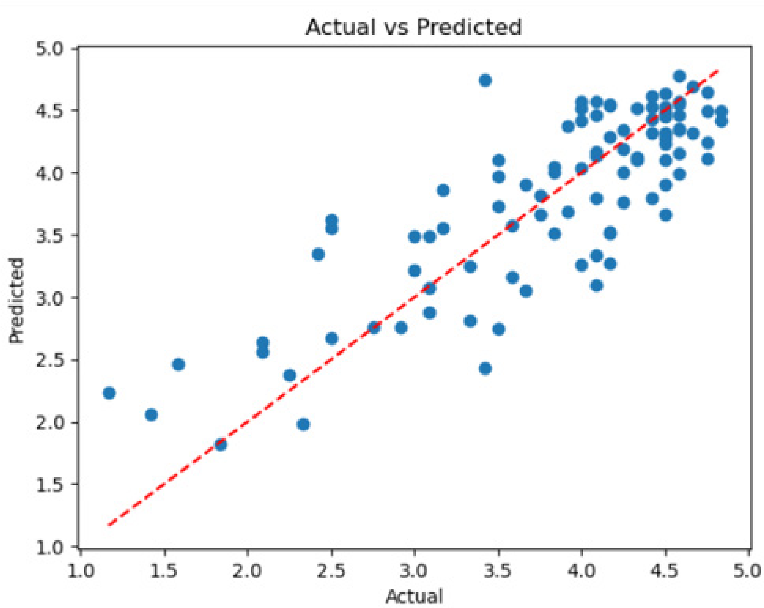

Fig. 7: Actual and Predicted Values Through MaxAbsScaler Normalization

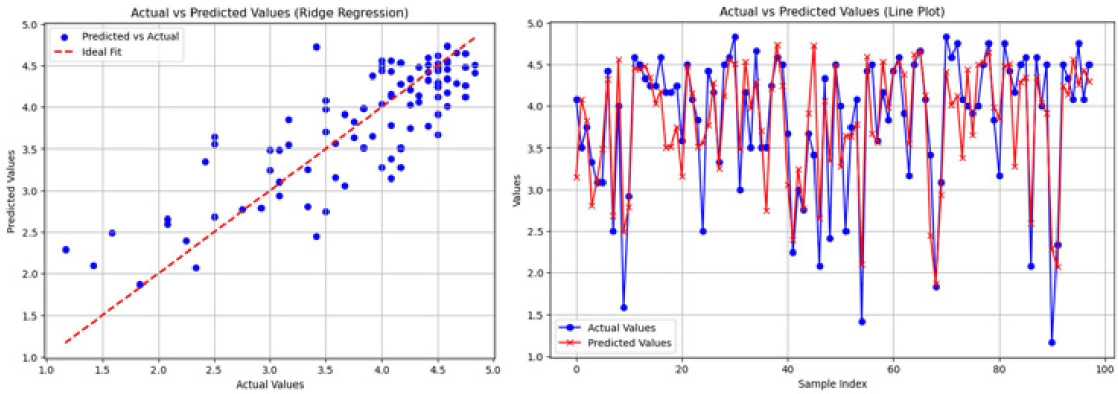

Fig. 8: Accuracy of Ridge Regression in Predicting Actual Test Data

(See Fig. 7).

Results of the Ridge Regression Algorithm

This algorithm employs Ridge Regression to predict the target variable (Y) based on the features of the data. After loading the data, it was split into two parts: training (80%) and testing (20%). The data was then normalized using MaxAbsScaler to ensure that the feature values were within an appropriate range. The Ridge Regression model was trained with an alpha parameter of 1.0, which controls the strength of L2 regularization. L2 regularization works by adding a penalty to the sum of the squared coefficients, preventing overfitting and ensuring the model is not excessively sensitive to the training data. The evaluation results of the model show that on the training data, the model has an MSE of 0.1816 and an R^2 Score of 0.6826, meaning that approximately 68.26% of the variance in the training data is explained by the model. According to the test data, the MSE is 0.2248, and the R^2 Score is 0.6792, indicating relatively good model performance and no overfitting, as evidenced by the small difference between the training and testing accuracies. The Actual vs Predicted plot shows the actual values against the predicted values, and the proximity of the points to the red line (Ideal Fit) indicates the high accuracy of the model's predictions (See Fig. 8). Overall, the model performs well and generalizes effectively.

Results of the Polynomial Regression Algorithm:

In this analysis, a polynomial regression model of degree 4 was used to predict the target variable. The data were first standardized to ensure uniform scaling of the features, followed by the creation of polynomial features up to degree 4. A linear regression model was trained on the training data and evaluated on the test data. The best model was selected based on the R^2 coefficient, which was found to be 0.4446. This value indicates that approximately 44.46% of the variation in the target variable is explained by the model.

Additionally, the Root Mean Squared Error (RMSE), a metric for evaluating the error, was calculated to be 0.5818, reflecting the deviation of the model's predictions from the actual values. Based on these results, it can be concluded that the current model has a relatively weak ability to predict the target variable. Furthermore, when the degree of the polynomial was reduced to 3, the accuracy decreased to 25.85, and with a degree of 2, it further dropped to 32.12, both of which represent lower and weaker accuracy values for the model. Additionally, in this algorithm, the iterations were performed 10 times for each model, which refers to the number of times the model is trained and evaluated on different data splits. Based on this approach, the model that performs the best on the test data is selected from the trained models. By creating multiple models based on different data splits, it is ensured that the obtained results are not random and that the model generalizes well. As observed from the graphs, the worst model accuracy occurred during the fourth iteration.

Continuing with this approach, if the degree is adjusted only to use linear features, the results will significantly improve. The interpretation of the results in this case indicates that the model's accuracy (R^2 Score) increases to approximately 72.1%, meaning that the model can explain 72.1% of the variance in the data. This is a good result. Additionally, the RMSE error decreases, indicating that the data tends to be linear and that the model can be predicted more accurately in a linear manner. Therefore, based on all the analyses conducted in previous cases, it can be stated that predictions in a nonlinear setting were highly inefficient and yielded low accuracy. Fig. 9 compares the actual values (y_test) with the predicted values (y_pred). The blue points on the plot represent the actual values versus the predicted values. The dashed black line (Ideal Fit) indicates the relatively ideal scenario where the predicted values are close to the actual values.

The figure related to the error distribution illustrates the distribution of the model's errors, which were calculated by subtracting the predicted values (y_pred) from the actual values (y_test). Using a histogram and Kernel Density Estimate (KDE) curve, the distribution of these errors is visually represented. As shown, the large errors are concentrated around the zero point, indicating that the model, in its first-degree setting, has been well-trained and its predictions are close to the actual values. Additionally, the concentration of errors around zero indicates that the model, on average, has a small error, and the predictions are not

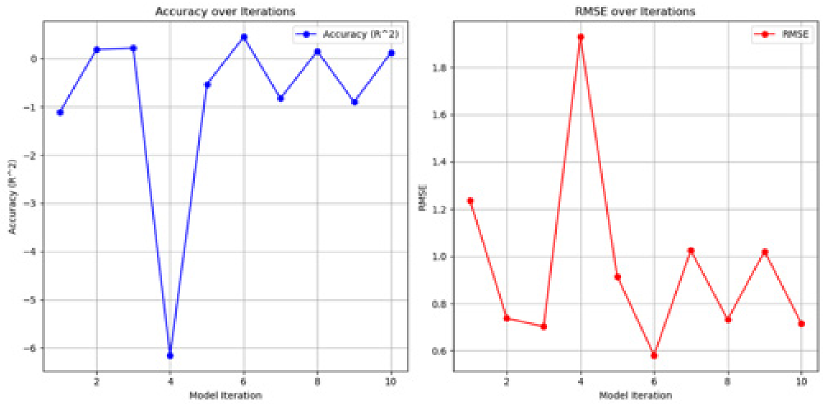

Fig. 9: Number of Model Training Iterations and Evaluations

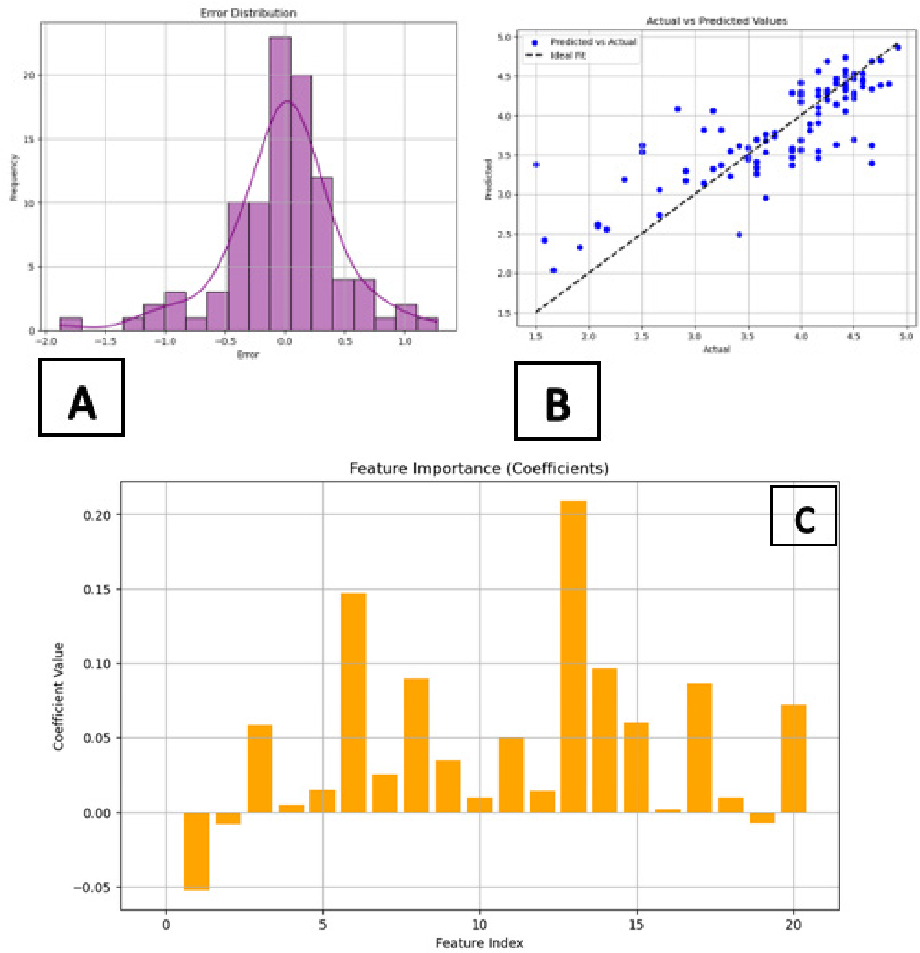

Fig. 10: (A) Comparison of Actual and Predicted Values, (B) Error Distribution, and (C) Features Importance

systematically higher or lower than the actual values.

In Fig. 10, the bar chart displays the coefficients of the model, representing the impact of each environmental characteristic on the target variable. The height of the bars indicates the importance of each feature in the model. This chart shows that features such as Positive home experiences, freedom from confinement, and Adequate bedroom size have the highest coefficient values in predicting the sense of place attachment.

Comprehensive Comparison of Algorithms in This Study

A comparison of Linear Regression, Ridge Regression, and Polynomial Regression highlights the distinct strengths and weaknesses of each model. Linear regression is a simple and interpretable method that performs well on linear data; however, it struggles with nonlinear relationships and the issue of overfitting. Ridge Regression, by

Table 3: Comparison of the Three Algorithms Used in This Study Based on Various Parameters

Metric	Linear Regression	Ridge Regression	Polynomial Regression
Accuracy (R^2 Score)	63.51% (without normalization)	68.26% (training data)	44.46% (degree 4)
	67.77% (with normalization)	67.92% (test data)	72.1% (degree 1 - linear)
MSE	0.2259 (with normalization)	0.1816 (training data)	-
	-	0.2248 (test data)	-
RMSE	-	-	0.5818 (degree 4)
Regularization	None	L2 regularization (alpha=1.0)	None (degree 4)
Resistance to Overfitting	Moderate	High	Low (degree 4)
Model Complexity	Simple	Moderate	High (degree 4)
Execution Time	Low	Low to Moderate	High (with higher degrees)
Interpretability	High (direct coefficients)	Moderate (regularized coefficients)	Low (complex coefficients)
Performance on Linear Data	Good	Good	Poor (degree 4) Good (degree 1)
Performance on Nonlinear Data	Poor	Poor	Good (degree 4)

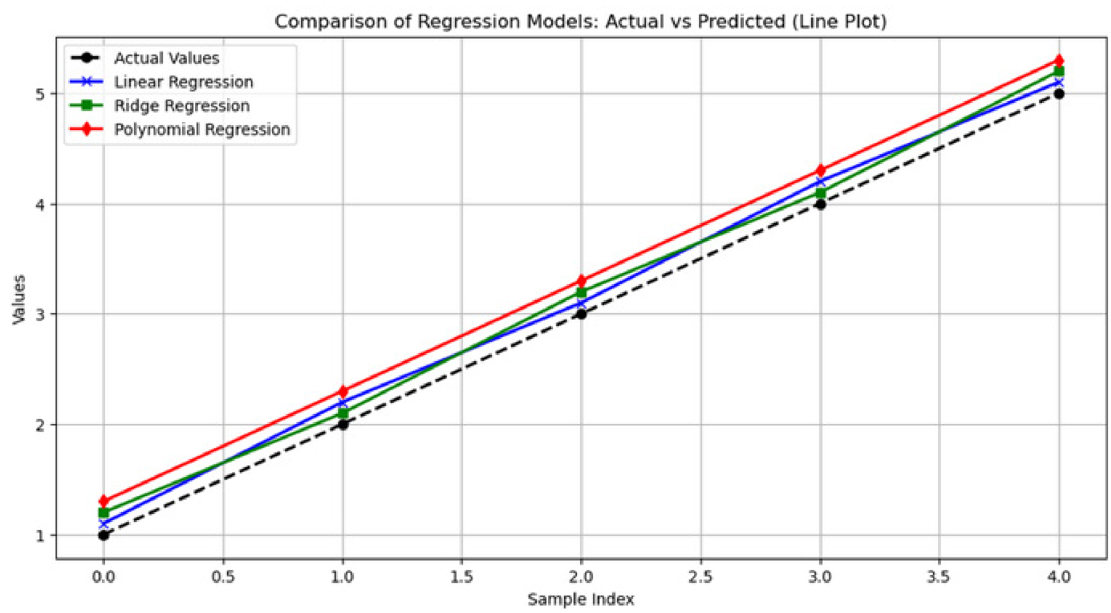

Fig. 11: Comparison of the Algorithms Used for Predicting Place Attachment

Table 4: Research Findings on the Current Housing Situation of the Elderly in the Selected Sample Size in Tehran

Approach	Influential Factor	Design Strategies in Physical, Emotional-Cognitive, and Social Dimensions
Enhancing a Sense of Attachment to Place	Physical and Architectural Factors	1. A private bathroom or toilet is attached to the bedroom. 2. The home provides access to a gym equipped with safety measures, a cinema, a shallow pool, a library, shopping centers, laundry services, art workshops, and psychological counseling services. Safety in home design is crucial. This includes preventing level differences on the floor to avoid tripping, using non-slip floor coverings, installing childproof outlets in the bathroom, and adding guards for windows and balconies. 4. Comfortable and tastefully furnished furniture for the elderly. 5. Avoid designing a space that is restrictive due to elements such as rooms and objects inside the house. 6. Easy and direct access to all spaces and facilities, such as the bathroom, toilet, living room, outdoor space, and other areas. 7. The possibility of easily decorating and changing room designs according to the preferences of the elderly. 8. Outdoor green spaces around the house offer the elderly the opportunity to enjoy nature's views from the comfort of their own homes. 9. Safe pathways, such as stairs, elevators, and ramps, should be provided to ensure wheelchair access and prevent falls and injuries. 10. The possibility of connecting personal rooms with communal spaces such as the living and reception rooms. 11. Comfort in heating, cooling, lighting, and sound. 12. Bedrooms should have adequate space to accommodate personal belongings, such as furniture, photo frames, and other unique items. 13. Embracing nature indoors through elements like potted plants, natural light, and fresh air, as well as creating green spaces through landscaping and design outdoors. 14. The design of public spaces includes family dining areas, private conversation spaces in the living room, and outdoor walking areas. 15. Connecting the home with nature and the surrounding open space, including walking paths, open areas, trees, and unrestricted views, with minimal fencing. 16. Easy access pathways for movement within the rooms. 17. Visually appealing, clean, and pleasantly scented home design. 18. Adequate access to natural light indoors. 19. Providing appropriate rehabilitation equipment for the elderly to perform personal tasks independently, such as handrails, wheelchairs, and standards related to elderly passage and access. 20. Designing sports spaces and providing facilities to promote health and well-being. 21. Designing gardening, artistic, and handicraft spaces based on the preferences of the elderly. 22. Designing spaces and facilities for functional activities such as cooking, exercising, recreation, relaxation, and bathing. 23. Enhancing the readability and distinguishability of the interior space to facilitate the location of places and items. 24. Enabling the elderly to move freely and access essential equipment and areas. 25. Attention is given to defensible architecture and the importance of security within the space. 26. Ensuring personal privacy in private spaces and avoiding interference from others. 27. The uniqueness of the home. 28. The possibility of experiencing sensory interactions with the surrounding environment and reminiscing about memories. 29. Engaging in social interactions and having communal spaces in the neighborhood enhance learning experiences. 30. Designing spaces that can facilitate meaningful activities at home and in the neighborhood, such as charity, communication, childcare, exhibiting works, and caring for plants and animals. 31. Neighborhood landscaping involves social participation and interaction with residents, family, friends, and acquaintances.

incorporating L2 regularization, offers superior performance compared to Linear Regression, including higher accuracy, lower mean squared error (MSE), and greater resistance to overfitting, making it a robust choice for linear data. On the other hand, Polynomial Regression performed poorly in modeling nonlinear relationships related to place attachment in this study.

In summary, Ridge Regression, as the most balanced model for predicting linear data in this study, offers a combination of accuracy and robustness, whereas Polynomial Regression shows weaknesses in handling nonlinear data. Linear regression, although a reliable baseline model, generally fails in most scenarios compared to Ridge Regression.

Additionally, the following chart compares the overall performance of the three algorithms used in this study to predict place attachment. The red color represents Polynomial Regression, the blue color represents Linear Regression, and the green color represents Ridge Regression. The distance of these lines from the black dashed line indicates the accuracy of the algorithms in predicting the actual data. As shown in Fig. 11, among the three algorithms, Polynomial Regression exhibits the weakest performance, while Ridge Regression provides the best performance.

Given that the specialized focus of this research lies within the realm of architecture, a more detailed examination is conducted on the physical and architectural aspects. Exploring the research question, "How can the physical and spatial elements enhance the sense of home and attachment to place among residents of new elderly housing?" It is worth noting that multiple tangible and mental factors are involved in this domain. These factors can be categorized into five groups: interior design and facilities, including dedicated bathrooms or toilets, access to various amenities such as a gym, cinema, and various services; safety and security, encompassing secure home design and safety equipment such as window guards and fences; comfort and convenience for the elderly, including comfortable furniture, the ability to make changes to the décor according to the elderly's preferences, and easy access to all facilities; Connection with nature, involving interaction with outdoor green spaces, design with natural light, and access to natural environments; and collective and social activities, comprising the design of spaces for meaningful activities, interaction with neighbors, and learning experiences. These categories are detailed in Table 4 below, summarizing all the design solutions related to the physical and architectural aspects of the project.

CONCLUSION

This study aimed to identify environmental features related to the sense of home and their impact on place attachment, as well as to find the best machine learning algorithm model for predicting place attachment in the personal housing of the elderly in Tehran. The goal was to assess the role of environmental features in accurately determining the primary objective (place attachment).

This study was based on three main questions, the first of which was the role of physical environmental factors in shaping the sense of home and its impact on place attachment among the elderly. Based on the research background, 20 key items were identified, including Private bedrooms with dedicated bathrooms, Recreational and community facilities, Safety features, Functional living spaces, Comfortable furniture and decorations, freedom from confinement, Accessibility, Flexible décor, Green spaces and nature views, Safe pathways, integration of private and communal spaces, Optimal comfort, Positive home experiences, Adequate bedroom size, nature indoors and outdoors, Public areas for diverse activities, connection to natural surroundings, Easy navigation, cleanliness and aesthetics, and Daylight access. These items are related to environmental design and contribute to creating a sense of home for the elderly, thereby influencing their sense of place attachment.

Based on the findings of this study, certain variables exhibited stronger correlations with one another. The item "Private bedrooms with dedicated bathrooms" had the strongest correlations with the items "Safety features" and "Safe pathways." Additionally, "Positive home experiences" showed a high correlation with "Freedom from confinement" and "Place attachment." On the other hand, some variables, such as "Daylight access," showed weaker correlations with other variables, for example, with "Recreational and community facilities." These findings suggest that improving certain features, such as Safety and Freedom from confinement, could have a positive impact on residents' overall satisfaction and their attachment to the living environment.

Additionally, "Positive home experiences" and "Freedom from confinement" have the greatest impact on "Place attachment." This indicates that feelings of satisfaction and freedom within the living environment are the key factors in fostering place attachment. Furthermore, "Daylight access" and "Recreational and community facilities" had the least impact on place attachment. This suggests that while these factors are important, their influence is relatively smaller compared to other factors.

The second research question focused on how machine learning algorithms can be used to predict place attachment in the existing housing of the elderly. Based on the steps carried out in the study, this process was conducted in several stages: data collection, selection of target variables and features, data preprocessing, selection and implementation of algorithms, model training and evaluation, results review, and selection of the best model, followed by an analysis of the influencing factors.

Initially, demographic information, physical conditions, and environmental features related to place attachment were collected from elderly individuals in Tehran. This included 20 input variables (features), such as safety and positive life experiences. In the next step, the data was organized and prepared for use in the machine learning algorithm. This stage involved data entry, standardization, and converting textual data into numerical codes. Subsequently, three algorithms—Linear Regression, Ridge Regression, and Polynomial Regression—were applied. The data was then split into two sets: a Training Set (80%) and a Test Set (20%). The algorithms were trained on the Train group, and their prediction accuracy was measured on the Test data. Finally, the three algorithms were compared, and their performance was evaluated.

The third research question focused on the accuracy of the

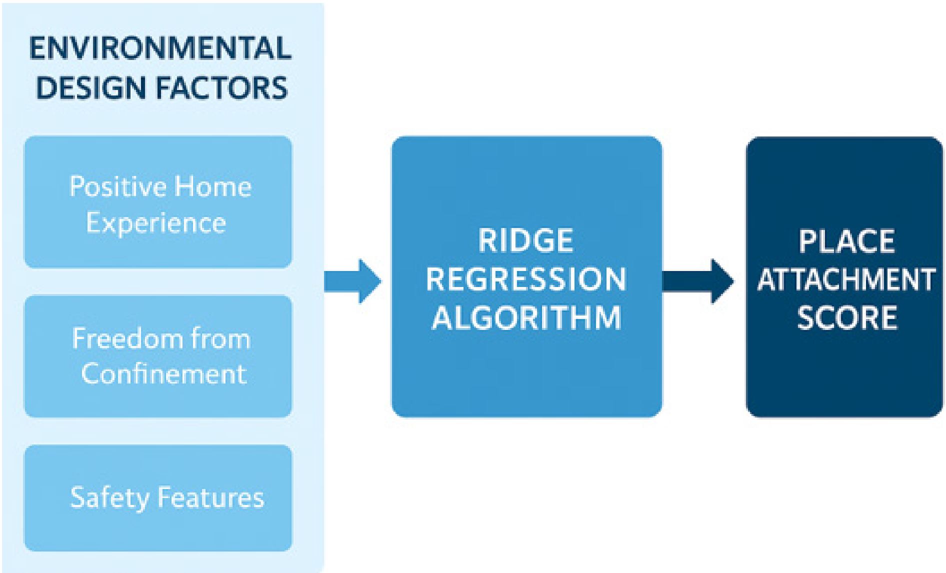

Fig. 12: A Predictive Framework for Place Attachment in Senior Housing with a Human-Centered Design Approach

algorithms used in predicting the target variable (place attachment). The results of evaluating these three algorithms indicated that Ridge Regression performed the best in predicting place attachment based on environmental variables influenced by the sense of home. In contrast, the Polynomial Regression algorithm yielded the weakest results for degrees 2 and above. Additionally, the model results showed that features such as Positive home experiences, freedom from confinement, and Adequate bedroom size had the highest coefficient values in predicting the level of place attachment.

This study makes a significant contribution to the field of Automation in Construction by integrating machine learning algorithms into the design and evaluation of elderly housing, thereby addressing a critical gap in personalized and supportive housing design. By employing Ridge Regression as the most effective predictive model ($R^2 = 0.6792$), the research demonstrates the potential of machine learning to enhance the accuracy of predictions regarding environmental and psychological factors influencing place attachment among the elderly. This approach not only aids in creating environments that meet physical needs but also improves residents' quality of life from psychological, social, and cultural perspectives. The findings emphasize the importance of incorporating human-centered design principles into construction processes, ensuring that architectural spaces are optimized for both functionality and emotional well-being. Furthermore, the application of these models in computer-aided design (CAD) systems can guide architects and planners in developing age-friendly urban environments, thereby promoting sustainable and efficient resource management.

Based on the findings, a conceptual framework was developed to visually and analytically demonstrate how specific environmental features—identified as significant predictors—interact with machine learning algorithms to produce a quantifiable measure of place attachment. This framework can assist in architectural design education, computer-aided housing design, and policy development for age-friendly environments (See Fig. 12).

The conceptual model illustrates a human-centered predictive framework for enhancing place attachment in senior housing. It is structured into three key components: (1) Environmental Design Inputs, such as positive home experiences, freedom from confinement, and safety features; (2) the application of Ridge Regression, a machine learning algorithm that demonstrated the highest prediction accuracy; and (3) the Place Attachment Score as the outcome. This model visually demonstrates how critical environmental factors can be quantitatively analyzed to inform personalized and age-friendly housing design. It serves as a practical tool for architects, urban planners, and educators aiming to integrate psychological well-being into architectural design.

Furthermore, this research highlights the role of automation in enhancing decision support systems for construction professionals. By leveraging data-driven insights derived from machine learning algorithms, stakeholders can make informed decisions about designing spaces that foster a sense of home and belonging among the elderly. For instance, features such as Positive Home Experiences, Freedom from Confinement, and Safety Features —identified as key predictors of place attachment—can inform the development of intelligent systems that prioritize user experience during the design phase. These systems could extend to automated inspection processes, robotics, and logistics in construction, ensuring that built environments align with human needs while maintaining cost-effectiveness and scalability. While the study is limited to Tehran's context, its methodology provides a foundation for broader applications across diverse cultural settings, encouraging the adoption of advanced algorithms, such as Deep Neural Networks or Random Forests, in future studies. Overall, this work highlights the transformative potential of interdisciplinary approaches at the intersection of environmental psychology and technology, paving the way for smarter, more empathetic designs in the construction industry.

This research, although it provides significant findings, also has several limitations. The focus of this study on the city of Tehran may limit the generalizability of its results to other cities or countries with different cultural and social conditions. The data in this study were collected through researcher-designed questionnaires, which may have been influenced by response bias, and the cross-sectional method used does not allow for examining long-term changes. The sampling of 490 elderly individuals from Tehran lacks sufficient demographic diversity and is limited. Moreover, the study relied on only three machine learning algorithms (linear regression, ridge regression, and polynomial regression); the use of more complex methods could have potentially improved prediction accuracy. Additionally, the primary focus of this study was on environmental and physical factors, with less attention given to social, psychological, and cultural factors. On the other hand, the prediction models may not perform optimally in other cultural or social areas due to differences in input data.

Future research could benefit from studies conducted in diverse environments, the application of advanced algorithms, and the integration of combined methods. It is recommended that future researchers employ advanced algorithms, such as Deep Neural Networks or Random Forests, to enhance prediction accuracy by combining different models. Furthermore, including physical housing data such as area, thermal comfort, height, and open space in the evaluation of elderly housing would improve the assessment. Additionally, examining changes in place attachment over time could provide better insights into the preferences of the elderly. It is also suggested that similar research be conducted in various cultures, communities, and human groups to achieve a more comprehensive and accurate assessment of individuals' environmental and psychological tendencies.

Ultimately, the findings of this research, by identifying essential environmental factors that shape the perception of "home," such as Freedom from Confinement, Safety, and Positive Home Experiences, and demonstrating their impact on place attachment, provide a deeper understanding of the relationship between environmental design and the psychological needs of the elderly. These results not only emphasize the importance of human-centered and personalized design in living spaces and housing for the elderly but also provide a scientific and precise foundation for improving their quality of life and well-being.

AUTHOR CONTRIBUTIONS

M. Olfat performed the literature review and experimental design, analyzed and interpreted the data, prepared the manuscript text, and edited the manuscript.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

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