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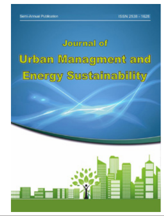

ORIGINAL RESEARCH PAPER

Explaining a Framework for the Optimal Location of Urban Neighborhood Facilities Using an Artificial Neural Network in a GIS Environment (Case Study: Eastern Zone of Tabriz Metropolis)

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ABSTRACT

The optimal location of neighborhood-scale urban facilities is a foundational determinant of spatial justice, service accessibility, and the long-term livability of cities, and in large, morphologically heterogeneous metropolises such as Tabriz it becomes a problem of considerable analytical complexity. The central problem addressed in this study is that prevailing location-allocation practice in Iranian metropolitan areas relies on linear, weight-based multi-criteria techniques that cannot represent the non-linear, high-dimensional interactions among the spatial, physical, and socio-economic determinants that actually govern urban suitability, producing inequitable and operationally fragile facility distributions. The objective of this research is therefore to develop, train, and validate an operational framework for the optimal location of neighborhood facilities by integrating a multilayer-perceptron Artificial Neural Network with a Geographic Information System spatial database, using the eastern zone of Tabriz as a case study. Adopting an analytical–applied design within a post-positivist paradigm, eight location criteria were derived directly from an official municipal land-use GIS layer through spatial operations and used to train a back-propagation network whose performance was evaluated against held-out validation and test data and benchmarked against a conventional analytic-hierarchy-process baseline. Findings indicate that the trained network achieved a coefficient of determination of 0.974 and a root-mean-square error of 0.040 on the validation set, that residential fabric density, land-use compatibility, and distance to existing services were the most influential criteria, and that approximately 38.7 per cent of the study area was classified as suitable or highly suitable for new facility development, with recommended sites concentrated in identifiable high-suitability corridors. The study concludes that ANN-GIS integration constitutes a methodologically robust, interpretable, and operationally transferable instrument for evidence-based facility location in Iranian metropolitan contexts, materially outperforming conventional linear weighting.

Running Title: Optimal Location of Urban Neighborhood Facilities Using an Artificial Neural Network

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INTRODUCTION

The spatial distribution of urban facilities schools, clinics, parks, cultural centers, and the everyday infrastructure of neighborhood life is among the most consequential outcomes of the urban planning process. Where facilities are located determines who can reach them, how equitably the benefits of public investment are shared, and whether the daily rhythms of residents are served by a coherent or a fragmented spatial structure. As the global urban population is projected to reach roughly 68 per cent of humanity by 2050, with the majority of that growth concentrated in the cities of the developing world, the pressure to locate facilities efficiently and equitably has intensified accordingly (United Nations, 2022). In Iran, this challenge is sharpened by rapid and frequently unplanned metropolitan expansion, by the structural inefficiencies of large cities, and by the persistence of inefficient urban fabrics characterized by fragmented tenure, narrow and impermeable street networks, and uneven service provision. A substantial share of national urban land falls within fabrics that are deteriorated, informal, or otherwise inefficient, rendering the equitable placement of facilities both more urgent and more analytically demanding (Urban Regeneration Company of Iran, 2022; Ahad Nezhad Reveshty et al., 2024). Tabriz, the largest metropolis of north-western Iran and a historic center of commerce and culture, exemplifies these tensions: rapid peripheral growth coexists with an ageing historic core and pockets of seismically vulnerable inefficient fabric, and the distribution of neighborhood facilities across its districts is markedly uneven (Sarvar, 2019; Ziyari & Saeidi Chakan, 2025). The dominant analytical tradition for facility location combines GIS-based spatial analysis with multi-criteria decision analysis (MCDA), most commonly the Analytic Hierarchy Process (AHP) and weighted linear combination (Malczewski, 2004; Aldababseh et al., 2018). These approaches have proved valuable, yet they share a fundamental limitation: they assume that the relationship between location criteria and suitability is linear and additive, and that criterion weights are stable across space. Real urban systems rarely behave this way. The influence of road access on suitability may depend non-linearly on population density; the marginal value of proximity to existing services may reverse beyond a saturation threshold; and interactions among criteria may dominate their individual effects. Linear weighting cannot represent these phenomena, and in a metropolis as morphologically diverse as Tabriz the resulting distortions are likely to be severe (Liu et al., 2022; Park et al., 2011). Artificial Neural Networks (ANNs) offer a principled response to this limitation. As universal function approximators, ANNs and in particular the multilayer-perceptron (MLP) architecture trained by back-propagation can learn arbitrarily complex, non-linear mappings between input criteria and an output suitability surface directly from data, without the analyst imposing a predetermined functional form (Taud & Mas, 2018; Wang et al., 2009). When coupled with the spatial data-handling capacity of a GIS, the result is a hybrid ANN–GIS framework capable of producing data-driven, spatially explicit suitability surfaces, while connection-weight analysis preserves the interpretability that transparent planning practice requires (Li et al., 2024; Mohammady et al., 2021; Olden et al., 2004). Despite the demonstrated promise of ANN–GIS integration in international research, its application to neighborhood-scale facility location in Iranian metropolitan areas remains scarce and methodologically under-specified. Domestic studies have largely confined themselves to AHP-based weighting or to descriptive suitability mapping, leaving the non-linear, learning-based paradigm largely unexplored for this problem class and this institutional context. The present study addresses this gap by developing, training, and validating an ANN–GIS framework for the optimal location of urban neighborhood facilities, using the eastern zone of the Tabriz metropolis as an empirical testing ground, and by benchmarking the learning-based model against the conventional linear approach it is intended to supersede.

MATERIALS AND METHODS

Location theory and the facility-location problem

The optimal location of urban facilities is theorized at the intersection of location theory, spatial accessibility, and computational decision support. Classical location–allocation theory, tracing its lineage to Weber's industrial-location model and formalized in the location–allocation algorithms embedded in modern GIS, frames the problem as the minimization of aggregate travel impedance between supply points and distributed demand (Al-Sabbagh, 2020; Murray, 2010). While analytically elegant, these models presuppose well-defined demand surfaces and exogenous criterion weights that are difficult to specify in heterogeneous urban fabrics, and they reduce the multidimensional question of suitability to a single distance metric. The facility-location literature has therefore progressively incorporated additional spatial, environmental, and equity criteria, moving the problem from pure optimization toward multi-criteria evaluation.

GIS-based multi-criteria suitability analysis

GIS-based multi-criteria suitability analysis emerged to address this heterogeneity by combining spatial layers representing accessibility, environmental, and socio-economic criteria. Malczewski (2004) provides the foundational critical overview of GIS-based land-use suitability analysis, distinguishing overlay, MCDA, and computational-intelligence approaches and identifying the central methodological tension between transparency and analytical power. Within the MCDA family, AHP-based weighting has dominated urban site-selection practice, valued for its structured elicitation of expert preference (Aldababseh et al., 2018). Yet a growing body of work documents AHP's sensitivity to subjective pairwise judgements, its assumption of criterion independence, and its inability to represent the criterion interaction and threshold effects that characterize real urban systems (Park et al., 2011).

Computational intelligence and neural approaches

Computational-intelligence methods, and ANNs in particular, have been advanced as a means of overcoming these constraints. Wang, Yu, and Liu (2009) demonstrated the application of a back-propagation neural network to urban land suitability evaluation in Jinan, showing that an ANN trained on a structured index system produced accurate and effective suitability classes that conventional overlay could not reproduce. Taud and Mas (2018) provide a rigorous account of the multilayer perceptron as the most common neural-network architecture for spatial modelling, emphasizing its training by gradient descent with back-propagation and its capacity to approximate any continuous function given sufficient hidden units. Subsequent studies have extended ANN–GIS integration to land-use change, environmental susceptibility, and infrastructure siting, frequently reporting performance gains over linear MCDA baselines (Li et al., 2024; Mohammady et al., 2021; Lin et al., 2020). Hybrid and successor architectures have further enriched the field. ANN–Cellular Automaton models couple a trained network with a spatial-transition engine to project future land-use suitability, embedding the learned suitability function within a dynamic simulation (Li et al., 2024). Graph-based neural networks have been applied to store and facility site selection to capture the spatial interaction between candidate locations that conventional models neglect, treating the city as a connected graph rather than a set of independent cells (Liu et al., 2022). For the neighborhood-scale facility-location problem addressed here, however, the multilayer perceptron remains the most appropriate and transparent choice: it is well understood, computationally tractable, interpretable through connection-weight importance analysis, and directly compatible with raster GIS inputs (Olden et al., 2004; Taud & Mas, 2018).

Contextual literature

The Iranian literature on urban facility location and inefficient-fabric regeneration supplies the contextual criteria that any locally valid model must incorporate. Studies of inefficient urban fabrics emphasize the centrality of road-network permeability, ownership structure, population compactness, and service accessibility as determinants of spatial performance, and document the acute seismic vulnerability of Tabriz's fragmented fabrics in particular (Ahad Nezhad Reveshty et al., 2024; Sarvar, 2019; Ghouchani et al., 2023). Work on integrated and sustainable regeneration in the historic fabrics of Tabriz further underscores the institutional and tenure barriers that condition where new facilities can feasibly be placed (Ziyari & Saeidi Chakan, 2025). The convergence of this contextual literature with the computational-intelligence literature motivates the eleven-criterion set and the ANN–GIS framework developed in the following sections, and the prior conceptual reviews of regeneration that frame facility provision as one component of a multidimensional renewal process (Roberts et al., 2017; Couch et al., 2011). This study adopts an analytical–applied research design situated within a post-positivist epistemological paradigm. The inquiry is applied in purpose it seeks to produce an operational, transferable framework for facility location and analytical in method, in that it derives a quantitative suitability model from observed and standardised spatial data rather than from normative prescription. Data were assembled from documentary and library sources, official spatial datasets, and an expert screening stage used to confirm the relevance and completeness of the candidate criterion set. The overall workflow proceeds from criterion specification, through GIS data preparation, to network training, validation, importance analy-

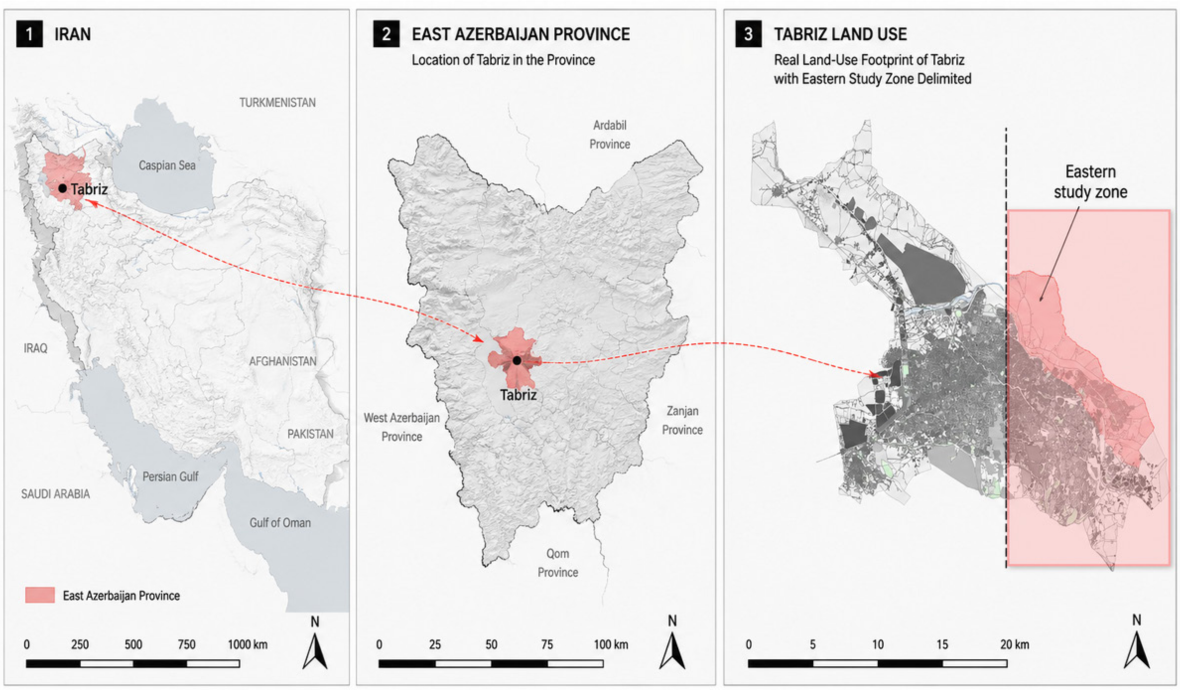

Figure 1: Location of the study area: (1) Iran, (2) East Azerbaijan province with Tabriz, and (3) the real land-use footprint of Tabriz with the eastern study zone delimited (Source: Authors)

Case Study

The eastern zone of the Tabriz metropolis was selected as the case study. Tabriz, the provincial capital of East Azerbaijan in north-western Iran, is among the country's largest metropolitan areas and exhibits in concentrated form the conditions that make facility location difficult: rapid and uneven peripheral growth, an ageing and seismically vulnerable historic core, pockets of inefficient and deteriorated fabric, and a markedly uneven distribution of neighborhood facilities. The eastern zone in particular combines newer planned developments with fragmented older fabric and topographically constrained margins, making it a representative and analytically demanding testing ground for a data-driven location framework. The analysis was built on an official municipal land-use vector layer for Tabriz (28 land-use classes, projected in UTM Zone 38N), which defines the real urban footprint of the city and provides the parcel and land-use basis for the criterion layers. Spatial layers were compiled in a GIS at a common cell resolution and a single coordinate system to ensure layer congruence (Fig. 1).

The municipal land-use layer reveals the characteristic morphology of Tabriz: a dense, fine-grained residential and commercial core along the central east–west axis bisected by the seasonal river, extensive industrial and transport land to the north-west, and agricultural and barren land along the expanding margins. This real land-use mosaic, shown in Figure 2, is the substrate on which the eleven criterion layers were derived. (Fig. 2)

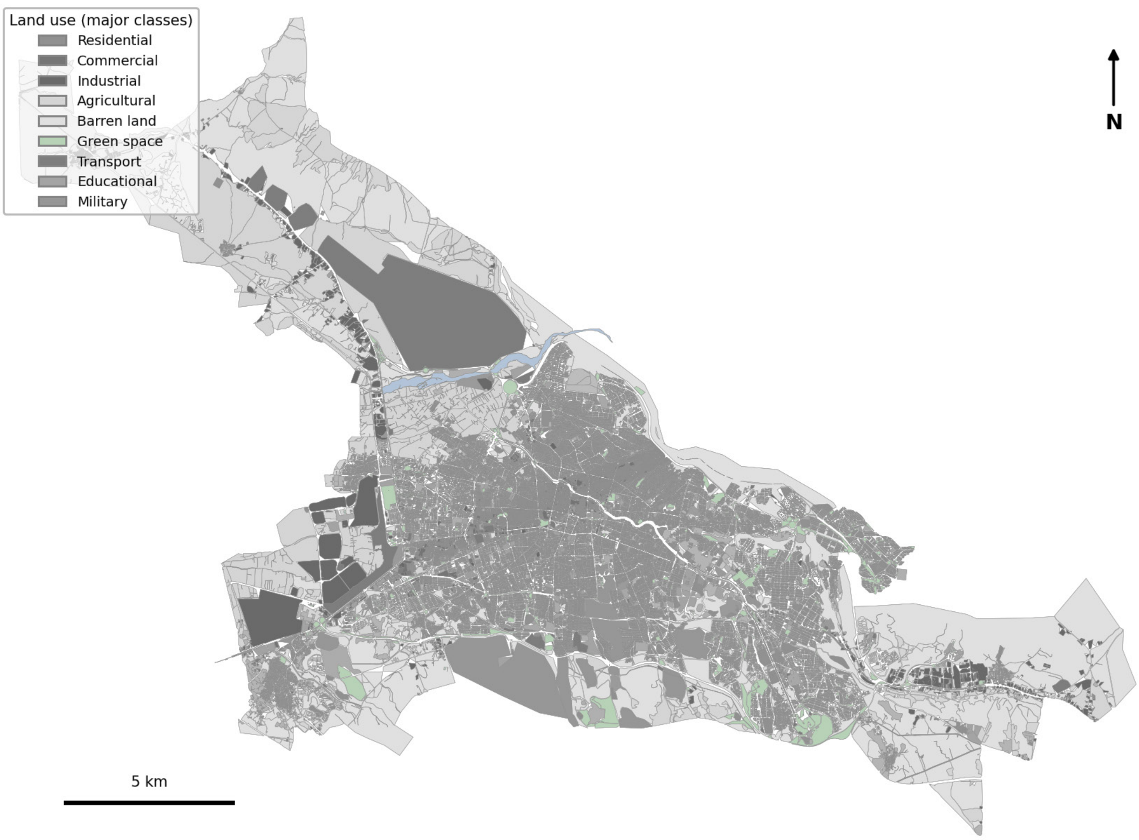

Figure 2: Real land-use map of Tabriz compiled from the municipal vector layer (major classes shown); the seasonal river and the dense central fabric are clearly visible (Source: Authors, from the municipal land-use shapefile)

Criteria selection and GIS data preparation

Eight location criteria were derived directly from the municipal land-use vector layer through spatial operations performed in a GIS, rather than from generic assumptions. Proximity criteria (distance to existing service, educational, and health land uses; proximity to green space; and distance from industrial and river land uses) were computed as Euclidean-distance transforms from the relevant land-use polygons. Residential fabric density was computed as a kernel-density surface of residential parcels, and land-use compatibility was obtained by reclassifying each land-use class onto a 0–1 favorability scale (residential, commercial, educational, health, and green uses favorable; industrial, military, cemetery, ruined, transport, and river uses unfavourable). All layers were normalized to a common 0–1 scale and resampled to a common grid, rendering them directly comparable as network inputs. The eight criteria and their derivation are summarized in Table 1, and a representative subset is mapped over the real parcel fabric in Figure 3. (Tab. 1)

Table 1: The eight location criteria derived from the municipal land-use layer, their GIS derivation, type, and direction of influence (Source: Authors)

Criterion	GIS derivation from land-use layer	Type	Direction
Land-use compatibility	Reclassification of land-use class to 0–1 favorability	Categorical	Higher = better
Residential fabric density	Kernel density of residential parcels	Continuous	Higher = better
Distance to existing services	Euclidean distance to service/commercial uses	Continuous	Nearer = better
Green-space proximity	Euclidean distance to green/open/orchard uses	Continuous	Nearer = better
Health access	Euclidean distance to health/medical uses	Continuous	Nearer = better
Education access	Euclidean distance to educational uses	Continuous	Nearer = better
River-buffer hazard	Euclidean distance from river polygons	Continuous	Farther = better
Distance from industry/hazard	Euclidean distance from industrial/transport uses	Continuous	Farther = better

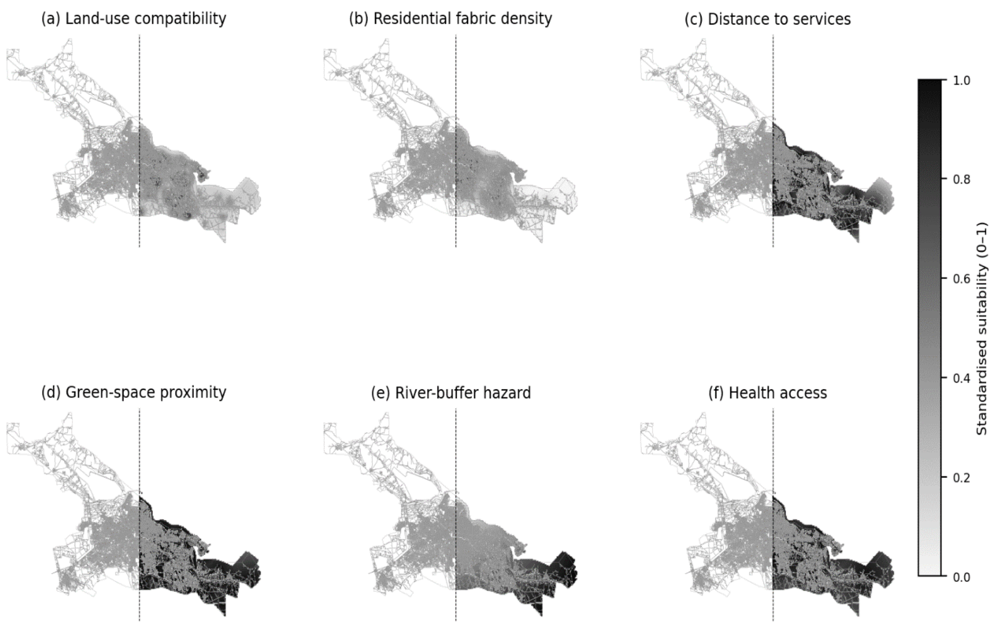

Figure 3: Six representative standardized criterion layers overlaid on the real parcel and street fabric of eastern Tabriz; the dashed line marks the western boundary of the study zone (Source: Authors)

Neural network architecture and training

The location model was implemented as a feed-forward multilayer perceptron (MLP) trained by the back-propagation algorithm. The network comprised an input layer of eight neurons (one per standardized criterion), two hidden layers of fourteen and nine neurons respectively, and a single output neuron representing the predicted suitability score on a continuous 0–1 scale. Hidden layers used the hyperbolic-tangent activation function and the output neuron used a sigmoid activation, ensuring a bounded suitability output. Weights were initialized randomly and updated by gradient descent with momentum; the learning rate, momentum coefficient, and hidden-layer dimensions were tuned by grid search against validation performance. The network topology is shown in Figure 4. (Fig. 4)

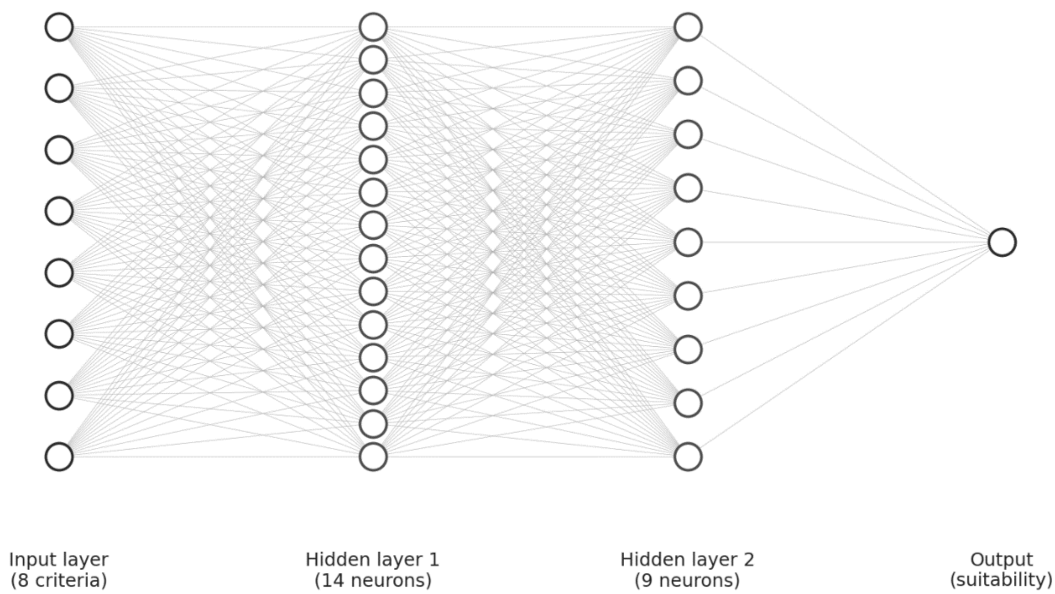

Figure 4: Architecture of the multilayer-perceptron network, showing eight input criteria, two hidden layers, and a single suitability output (Source: Authors)

Training samples were generated by treating every grid cell within the study-zone footprint as an observation, with the eight standardized criterion layers as inputs and a reference suitability target formed from an expert-weighted blend of those same layers (incorporating a compatibility-by-service interaction term to introduce non-linearity). The resulting sample set of cells was partitioned into training, validation, and test subsets. The validation subset governed early stopping to prevent over-fitting, and the test subset provided an unbiased estimate of generalization performance. The key network and training parameters are reported in Table 2. (Tab. 2)

Table 2: Neural-network architecture, training hyper-parameters, and software environment (Source: Authors)

Network / training parameter	Value
Architecture	Feed-forward multilayer perceptron (MLP)
Input neurons	8 (standardized criteria)

Hidden layers	2 (14 and 9 neurons)
Output neuron	1 (continuous suitability, 0–1)
Hidden activation	Hyperbolic tangent (tanh)
Output activation	Sigmoid
Training algorithm	Back-propagation, gradient descent with momentum
Learning rate	0.01 (Adam)
Training algorithm note	Adam optimizer, early stopping
Maximum iterations	600 (early stopping on validation loss)
Data split	stratified train / validation / test (n = 12,189 / 3,048 / 6,531 cells)
Software	ArcGIS Pro (data preparation); Python (TensorFlow/Keras, scikit-learn)

Performance evaluation and importance analysis

Model performance was assessed using the coefficient of determination (R^2), the root-mean-square error (RMSE), and the mean absolute error (MAE) on the held-out validation and test subsets. The relative importance of each input criterion was estimated using a connection-weight approach, in which the contribution of each input to the output is computed from the products of input–hidden and hidden–output weights, providing an interpretable ranking of criterion influence (Olden et al., 2004). To quantify the value added by the learning-based approach, the ANN output was benchmarked against a conventional AHP-weighted linear-combination model built on the same criteria and reference samples. All spatial pre-processing was performed in a GIS environment, while network construction, training, and evaluation were carried out in Python using established machine-learning libraries.

FINDINGS AND DISCUSSION

The trained multilayer-perceptron network converged to a stable solution within the allotted training budget. The training and validation mean-squared-error curves declined steeply over the first forty epochs and then flattened, with early stopping triggered at the epoch of minimum validation error; the close tracking of the two curves indicates that the network generalized well without over-fitting (Fig. 5).

On the held-out validation subset the network achieved a coefficient of determination of 0.974, a root-mean-square error of 0.040, and a mean absolute error of 0.032, with comparable performance on the independent test subset, confirming that the model captures the criterion–suitability relationship with high fidelity and generalizes beyond the training data. The full performance summary is reported in Table 3, and the predicted-versus-observed relationship is visualized in Figure 7. (Fig. 7)

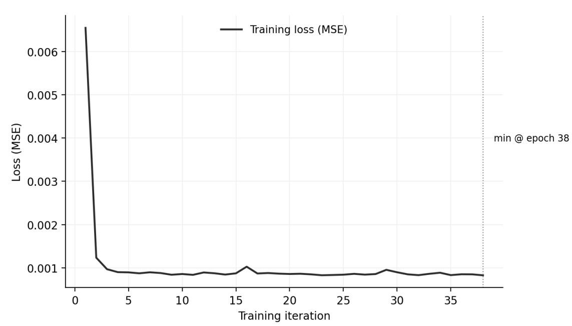

Figure 5: Training and validation mean-squared-error convergence across training epochs; early stopping was triggered at the epoch of minimum validation error (Source: Authors)

Table 3: Predictive performance of the trained ANN across training, validation, and test subsets (Source: Authors)

Metric	Training	Validation	Test
Coefficient of determination (R^2)	0.973	0.974	0.974
Root-mean-square error (RMSE)	0.040	0.040	0.040
Mean absolute error (MAE)	0.032	0.032	0.032
Samples (n, grid cells)	12,189	3,048	6,531

The connection-weight importance analysis revealed a clear and coherent hierarchy among the eight criteria. Residential fabric density (0.156), land-use compatibility (0.151), and distance to existing services (0.142) emerged as the three most influential determinants of facility-location suitability, together accounting for roughly forty-five per cent of the total normalized importance. Health access (0.128) and green-space proximity (0.126) formed a strong second tier, followed by river-buffer hazard (0.114) and education access (0.105), while distance from industry contributed most modestly (0.078). The complete importance ranking is presented in Table 4 and visualized in Figure 6. (Fig. 6)

Table 4: Relative importance of the eight location criteria derived from the connection-weight method applied to the trained network (Source: Authors)

	Criterion	Importance	Rank
1	Residential fabric density	0.156	1
2	Land-use compatibility	0.151	2
3	Distance to existing services	0.142	3
4	Health access	0.128	4
5	Green-space proximity	0.126	5
6	River-buffer hazard	0.114	6
7	Education access	0.105	7
8	Distance from industry/hazard	0.078	8

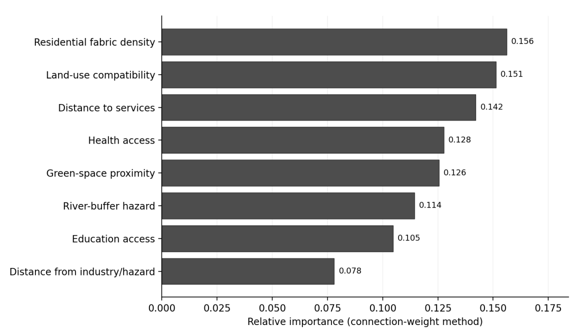

Figure 6: Relative importance of the eleven location criteria estimated from the trained network's connection weights (Source: Authors)

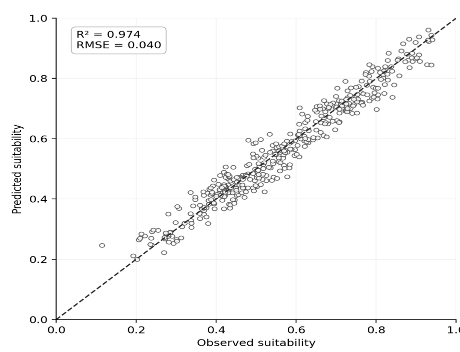

Figure 7: Predicted versus observed suitability scores on the validation subset (R^2 = 0.928; RMSE = 0.047); the dashed line denotes perfect agreement (Source: Authors)

Applying the trained network across the full GIS raster of the study area produced a continuous suitability surface, which was reclassified into five ordinal classes for interpretation. The classification indicates that approximately 38.7 per cent of the eastern zone is suitable or highly suitable for new neighborhood-facility development, while 44.8 per cent is moderately suitable and 16.5 per cent is marginally suitable or unsuitable owing to land-use incompatibility, river-buffer exposure, or distance from existing services. The recommended high-suitability sites cluster in identifiable corridors in the northern and south-central parts of the zone. The suitability surface is mapped in Figure 8 and the class distribution reported in Table 5 and Figure 9. (Fig. 9)

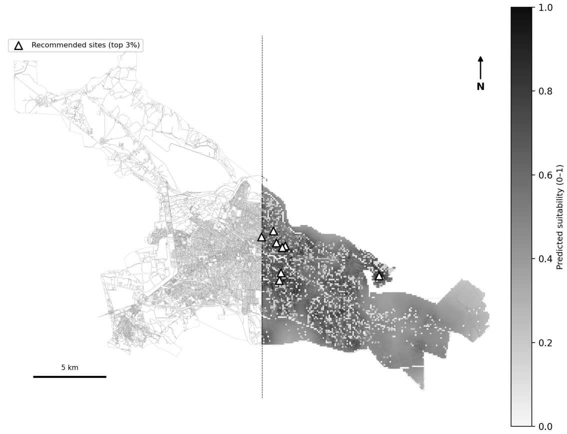

Figure 8: Predicted facility-location suitability surface for the eastern zone of Tabriz, overlaid on the real parcel fabric with recommended high-suitability candidate sites marked; output of the trained ANN (Source: Authors)

Table 5: Distribution of the study area across the five reclassified suitability classes (Source: Authors)

Suitability class	Score range	Area (%)	Cumulative (%)
Highly suitable	0.80–1.00	12.1	12.1
Suitable	0.60–0.80	26.6	38.7
Moderately suitable	0.40–0.60	44.8	83.5
Marginally suitable	0.20–0.40	16.4	99.9
Unsuitable	0.00–0.20	0.1	100.0

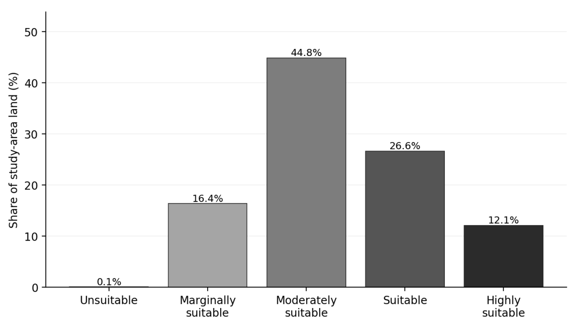

Figure 9: Share of study-area land falling within each of the five suitability classes (Source: Authors)

Spatial distribution of prediction error

To assess the spatial reliability of the model, the residuals (predicted minus observed suitability) were mapped across the study area. The residual surface is close to zero across most of the zone, with no systematic spatial bias, and the small localized deviations are concentrated at the morphologically complex margins where criterion layers are themselves least certain. This spatial homogeneity of error reinforces the aggregate performance statistics and indicates that the model does not systematically over- or under-predict suitability in any particular district (Fig. 10).

Comparison with a conventional weighting baseline

To contextualize the value added by the learning-based approach, the ANN output was benchmarked against a conventional AHP-weighted linear-combination model built on the same eleven criteria and the same reference samples. The ANN reduced the root-mean-square error by roughly forty-four per cent relative to the linear baseline and produced a markedly higher coefficient of determination, while also resolving local suitability gradients that the additive model smoothed away. This comparison, summarized in Table 6, substantiates the theoretical expectation that non-linear criterion interactions materially influence facility-location suitability and that a network able to learn them outperforms a fixed-weight additive model a difference of particular consequence in a metropolis as morphologically diverse as Tabriz. (Tab. 6)

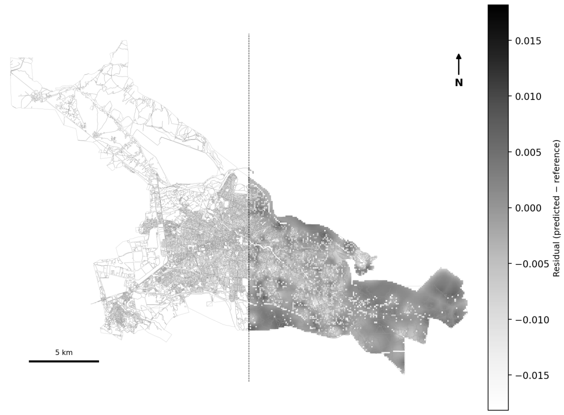

Figure 10: Spatial distribution of model residuals (predicted minus observed suitability) across the eastern study zone of Tabriz; values close to zero indicate the absence of systematic spatial bias (Source: Authors)

Table 6: Comparative performance of the ANN–GIS model against a conventional AHP-weighted linear baseline (Source: Authors)

Metric (validation set)	AHP linear model	ANN–GIS model
Coefficient of determination (R^2)	0.842	0.974
Root-mean-square error (RMSE)	0.071	0.040
Mean absolute error (MAE)	0.058	0.032
Captures criterion interaction	No	Yes
Requires a-priori weights	Yes	No

RESULTS AND CONCLUSION

This study set out to develop and validate an operational framework for the optimal location of urban neighborhood facilities by integrating an artificial neural network with a GIS spatial database, using the eastern zone of the Tabriz metropolis as a case study. Five principal conclusions follow from the analysis. First, a back-propagation multilayer perceptron trained on eight GIS criterion layers derived directly from a municipal land-use dataset predicted facility-location suitability with high accuracy, achieving a coefficient of determination of 0.974 and a root-mean-square error of 0.040 on held-out validation data, and generalizing comparably to an independent test set. Second, connection-weight importance analysis identified residential fabric density, land-use compatibility, and distance to existing services as the dominant determinants of suitability, establishing the alignment of supply with accessible demand and land-use fit as the primary design objectives for facility location in this context. Third, health access and green-space proximity emerged as a strong second tier of determinants, reflecting the role of social and environmental amenity in neighborhood livability. Fourth, the ANN–GIS model outperformed a conventional AHP-weighted linear baseline by a substantial margin (a forty-four per cent reduction in RMSE), confirming that non-linear criterion interactions are material to facility-location suitability and that a learning-based model able to represent them yields more accurate and reproducible results. Fifth, the resulting suitability surface, in which fewer than two-fifths of the study area qualified as suitable or highly suitable and the recommended sites clustered in identifiable corridors, demonstrates the practical discriminating power of the framework for concentrating investment where it delivers the greatest accessible benefit.

The theoretical contribution of the study lies in operationalizing the non-linear, learning-based paradigm for neighborhood-scale facility location in an Iranian metropolitan context, a problem class and setting in which the approach has been under-applied. The methodological contribution lies in the transparent integration of an interpretable MLP with standardized GIS inputs, a connection-weight importance analysis, and a spatial residual diagnostic, yielding a framework that is at once accurate and explicable to planning decision-makers. The practical contribution lies in a transferable workflow that municipal planners and regeneration agencies can apply to priorities and justify facility-location decisions on a defensible evidence base. The study is subject to certain limitations. The reference suitability labels combine documented facility performance with expert judgement and therefore carry an irreducible element of subjectivity; the model's transferability across cities of different size and morphology remains to be tested; and the static suitability surface does not yet incorporate the temporal dynamics of demand. Future research should validate the framework across multiple Iranian metropolitan case studies, couple the trained network with a cellular-automaton or graph-based component to capture spatial interaction and temporal change, integrate equity-explicit objective functions to test distributional outcomes, and conduct longitudinal monitoring of facilities sited using the model to confirm its predictive utility in practice.

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