Quantifying how a zone is residential

A Multi-Criteria Decision Making approach

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The COVID-19 pandemic has greatly impacted education, work dynamics, and social interactions. Allocating building utilities effectively during lockdowns is a challenge. Strategic resource allocation prioritizes residential areas over commercial ones based on population density. Accurately delineating residential zones is difficult due to complex urban landscapes. This paper discusses an indicator that uses open-source intelligence and a decision-making framework to assess the likelihood of an area being residential. The indicator optimizes resource allocation for power, gas, and water distribution. A case study in Nicosia, Cyprus, demonstrates its effectiveness.

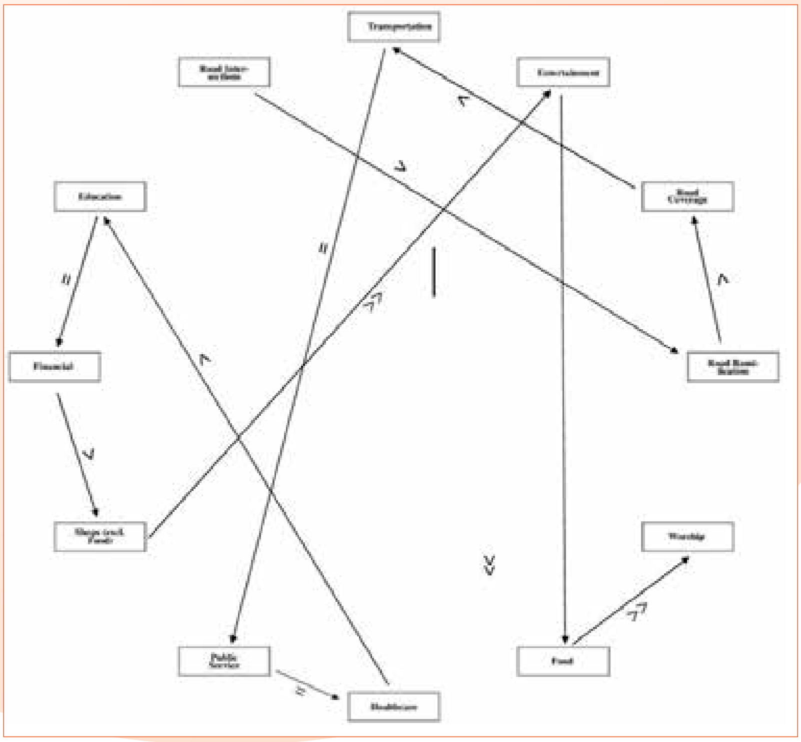


Fig. 1 - Example of a pictorial questionnaire filled by an expert.

Assessing the residential nature of an area in complex urban landscapes, especially in major cities, is challenging. However, quantifying residential likelihood would be valuable during crises or resource scarcity (Carlucci et al., 2021). For instance, in strict pandemic lockdowns or energy disruption scenarios, identifying residential areas becomes crucial for effective resource distribution and rationing policies.

This article reviews the work undertaken by NITEL and S3 within the EUMAP project (Oliva et al., 2021). In particular, the undertaken activities were aimed to develop a comprehensive indicator using open-source intelligence to assess residential likelihood.

Notably, if satellite information is directly used and integrated for this purpose, managing and optimizing the connection and data transfer aspects is highly beneficial (Belli et al., 2009, Abdelsalam et al., 2017, Abdelsalam et al., 2019).

In this paper we consider a complementary approach and, specifically, we rely on OpenStreetMap data (OpenStreetMap) obtained through OverPass APIs (Olbricht,2015) to identify indirect indicators like road network density, presence of shops, entertainment venues, places of worship, and financial facilities. Human decision-makers contributed their expertise to determine the indicators' relative importance, which we distill using the Incomplete Analytic Hierarchy Process technique (Bozóki et al. 2010, Oliva et al., 2017, Bozóki and Tsyganok, 2019, Oliva et al., 2019). These absolute utility values form the basis of a weighted sum, creating a holistic index for each zone.

Multi-Criteria Decision Model for Residential Area ùAssessment

In this section, we discuss the proposed Multi-Criteria Decision Model, including the metrics considered along with their weights derived from interactions with decision-makers. The metrics serve as indirect measures of residential likelihood and are obtained from public information sourced from OpenStreetMap via the Overpass APIs.

Let us consider a specific location j, defined by latitude latj and longitude lonj. We also define an "area of interest" surrounding the location, represented by the set of points h where lath ∈ [latj − Δlat, latj + Δlat] and lonh ∈ [lonj −Δlon, lonj + Δlon]. For this study, we consider Δlat and Δlon values corresponding to a one square kilometer bounding box centered on the location. The residential nature of an area in complex urban landscapes, especially in major cities, is challenging. However, quantifying residential likelihood would be valuable during crises or resource scarcity (Carlucci et al., 2021). For instance, in strict pandemic lockdowns or energy disruption scenarios, identifying residential areas becomes crucial for effective resource distribution and rationing policies. In the following, we list the indicators we considered as indirect measures of residential likelihood:

1. *Road Ramification*: Number of nodes in the area of interest, representing the road network's density (e.g., highways have fewer nodes, while densely populated neighbourhoods have multiple nodes).
2. *Road Intersections*: Number of nodes in the area of interest that correspond to road intersections (nodes with a degree greater than two).
3. *Road Coverage*: Total road length in the area of interest (highways generally have a single main road, while densely populated areas have multiple intersections).
4. *Food*: Total count of food-related shops (e.g., supermarkets, groceries, restaurants) in the area of interest.
5. *Financial*: Total count of finance-related facilities (e.g., ATMs, banks, currency exchange) in the area of interest.
6. *Education*: Total count of education-related facilities (e.g., colleges, driving schools, kindergartens) in the area of interest.
7. *Healthcare*: Total count of healthcare-related facilities (e.g., hospitals, clinics, dentists) in the area of interest.
8. *Entertainment*: Total count of entertainment-related facilities (e.g., art centres, cinemas, theatres) in the area of interest.
9. *Public Service*: Total count of public service facilities (e.g., courthouses, fire stations, post offices) in the area of interest.
10. *Worship*: Total count of worship facilities (e.g., churches, mosques, synagogues) in the area of interest.
11. *Transportation*: Total count of transportation-related facilities (e.g., bus stops, parking lots, taxis) in the area of interest.
12. *Shops (excluding Food)*: Total count of shops, excluding food-related establishments (e.g., clothing stores, hardware stores, stationery shops) in the area of interest.

Calculating the weights

We now discuss the computation of the metrics weights wi, which are essential for the holistic indicator used to assess the residential likelihood of a zone. Six decision-makers, including industry and academia experts with critical infrastructure analysis and management experience, were interviewed. To collect their opinions, a pictorial questionnaire was presented (see Figure 1), where experts indicated their preferences by drawing arrows and associating symbols from Saaty's scale (Saaty, 1990).

The symbols were translated into numerical values according to Saaty's scale (Table 1). The experts compared pairs of alternatives based on their comfort level, resulting in a disconnected graph in some cases. However, by combining the opinions of multiple decision-makers, a connected graph and proper ranking were obtained. Table 2 shows the weights wi associated with each metric which were computed using the Logarithmic Least Squares approach to solve the Incomplete Analytic Hierarchy Process problem, e.g., see (Oliva et

```
function [num_features] = getDataByType(bounding_box,type);
    area_to_request = bounding_box %area defined by two
   longitudes and two latitudes
    url = strcat('https://overpass-api.de/api/map?bbox=',
   area_to_request);
    map = urlread(url); %response from OSM
    data=xml2struct(map);%transforms xml into a Matlab
   Struct data type
    features = get_features_from_tags(data,type) %number of
   features of given type found in the specified area
    num_features = count_features(features) %number of
   occurrences per feature
```

Fig. 2 - Code snippet of the proposed MATLABTM implementation.

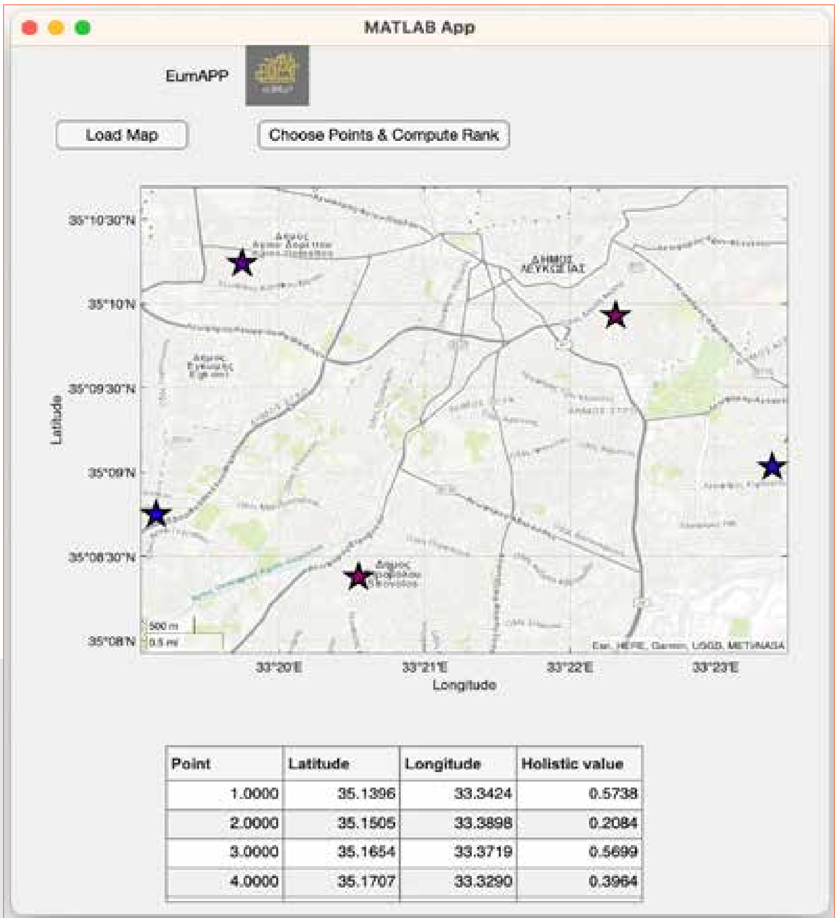
Referring to wi > 0 as the weight associated with the i-th criterion and cij as the value assumed by the j-th residential zone according to the i-th criterion (possibly normalized between zero and one), the holistic score for the j-th residential zone is given by:

$$C_j = \sum_{i=1}^{n} w_i c_{ij}$$

al., 2019). The total number of transportation-related facilities is considered the most important factor, contributing approximately 14.19% to the holistic metric. Conversely, the number of worship places is deemed the least important, contributing approximately 1.78% to the holistic metric.

Assessing the likelihood that a zone is residential

Consider a set of k alternatives, such as zones to be ranked based on their likelihood of being residential. Each zone is associated with n metrics or indicators that describe its importance according to a specific criterion.



Point	Latitude	Longitude	Holistic value
1.0000	35.1396	33.3424	0.5738
2.0000	35.1505	33.3898	0.2084
3.0000	35.1654	33.3719	0.5699
4.0000	35.1707	33.3290	0.3964

Fig. 3 - Graphical user interface.

Note that the scores cij are normalized in the interval [0,1] since the different metrics may have varying scales. Specifically, for each criterion h, we normalize the raw values craw using the min-max normalization technique (Patro and Sahu, 2015), a popular approach for normalizing features in machine learning applications.

Implementation

OpenStreetMap (OSM) is an open-source editable map database that provides geospatial information. The data is organized in features represented by tags, allowing users to access various physical elements such as buildings, forests, and more. The data can be retrieved through the OpenStreetMap Overpass API, which serves custom-selected parts of the map data. In this paper, MATLAB is used to implement a function that requests geo-referenced data for a specified geographical area using a bounding box.
The provided MATLAB™ language code snippet (Figure 2) demonstrates how the function retrieves the requested data and parses it into a Struct data type. The features are obtained based on predefined tags, such as clinics, theaters,

and restaurants, and the function returns the count of occurrences for each feature. Additionally, the code mentions that by selecting specific types like nodes and ways, it is possible to reconstruct the road network topology. Attributes like length can be obtained for each way, and the graph representation allows the identification of actual traffic intersections by selecting nodes with a degree greater than two.
Figure 3 shows the graphical user interface developed in order to support the user in the selection of the locations to be evaluated and compared. Specifically, the interface is developed in MATLAB™, using the App Designer interactive development environment.

Case Study

The effectiveness of the proposed framework is demonstrated through a case study in Nicosia, Cyprus. Five locations are considered, visually represented as stars on a satellite image (Figure 4). The latitude, longitude, and raw scores craw for the 12 metrics are provided in Table 3. The normalization results are shown in Table 4. The holistic indicator, obtained from the multi-criteria decision model, is presented in Table 5 for the five locations.
Based on the proposed holistic index, Location #4 is identified as the most important, while Location #3 is deemed the least important. These findings align with expectations, as Location #4 corresponds to the city center, while Location #3 is situated near a highway in the Strovolos area. Notably, Location #1, despite its proximity to the city center, receives lower scores compared to Location #2 (also in a central zone) in categories such as Food, Healthcare, Transportation, and Shops due to its adjacency to the Alsos Forest. Furthermore, Location #5, situated in an area with ministries and offices, exhibits a relatively low holistic indicator value.
Overall, the case study indicates that the proposed holistic index is effective in distinguishing between densely and sparsely populated zones.

Symbol	Value	Definition
=	1	Equal importance
>	3	Somewhat more important
>>	5	Much more important
>>>	7	Very much more important
>>>>	9	Absolutely more important

Tab. 1 - Saaty's ratio scale (Saaty, 1990).

Conclusions

This article discusses a holistic indicator for quantifying the residential likelihood of a zone, utilizing open-source intelligence and multi-criteria decision-making. The effectiveness of this approach is demonstrated through a case study conducted in Nicosia, Cyprus. The proposed index serves as a foundation for optimizing resource distribution, such as power, gas, or water.

Metric	Weight
Road Ramification	0.1187
Road Intersections	0.1012
Road Coverage	0.1322
Food	0.1005
Financial	0.0516
Education	0.1135
Healthcare	0.0821
Entertainment	0.0305
Public Service	0.0505
Worship	0.0178
Transportation	0.1419
Shops	0.0596

Tab. 2 - Table summarizing the weights wi associated with the 12 different metrics.

	Location #1	Location #2	Location #3	Location #4	Location #5
Latitude	35.159239	35.171152	35.129852	35.171897	35.15073
Longitude	33.358824	33.375084	33.362858	33.361405	33.374417
Road Ramification	2530	2219	1426	6799	1597
Road Intersections	2802	2196	1414	6471	1550
Road Coverage	6.6276×10^1	6.1285×10^2	1.9521×10^1	1.9280×10^2	5.0558×10^1
Food	6	16	1	126	7
Financial	2	2	0	20	4
Education	11	3	2	4	6
Healthcare	1	15	2	3	2
Entertainment	2	3	0	5	1
Public Service	0	0	0	9	0
Worship	1	1	1	13	0
Transportation	5	19	4	37	5
Shops	1	30	8	49	14

Tab. 3 Table summarizing the latitude, longitude and raw scores craw of the five considered locations. (source (Oliva et al., 2022)).

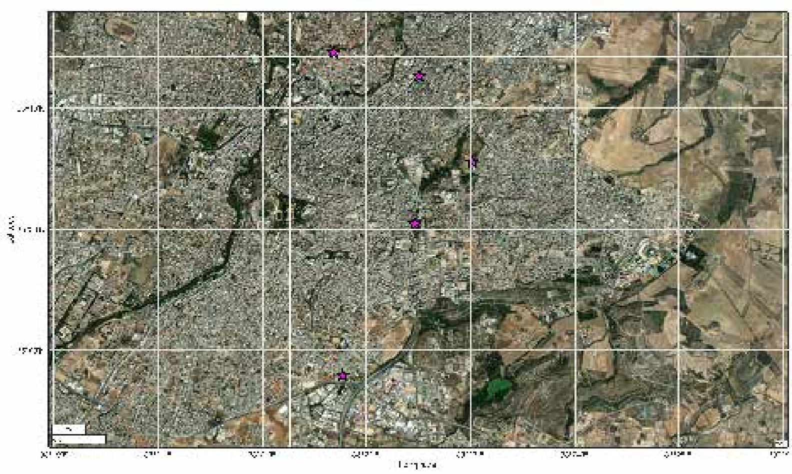


Fig. 4 - Satellite map of the city of Nicosia, Cyprus, showing the five considered locations as magenta stars (source (Oliva et al., 2022).

Future work aims to enhance the model by incorporating additional features, such as road types (one-way or two-way), and exploring other types of infrastructures, including telecommunications base stations and electrical power cabins within a zone. Additionally, the possibility of assessing the residential likelihood for zones of varying sizes will be explored, along with investigating automatic parameter tuning based on specific city characteristics.

	Location#1	Location#2	Location#3	Location#4	Location#5
Road Ramification	0.2613	0.1176	0	1	0.0518
Road Intersections	0.2745	0.1425	0	1	0.0256
Road Coverage	0.1169	0.0821	0	1	0.0072
Food	0.0400	0.1200	0	1	0.0480
Financial	0.1006	0.1500	0	1	0.2500
Education	[illegible]	0.1111	0	0.2222	0.1444
Healthcare	0	1	0.0714	0.1429	0.0714
Entertainment	0.4000	0.6000	0	1	0.2000
Public Service	0	0	0	1	0
Worship	0.0769	0.0769	0.0769	1	0
Transportation	0.0303	0.4545	0	1	0.0606
Shops	0	0.6042	0.1458	1	0.2708

Tab. 4 - Table summarizing the normalized scores cij of the five considered locations according to the 12 different considered metrics (source (Oliva et al., 2022)).

	Location#1	Location#2	Location#3	Location#4	Location#5
Holistic Index	0.2147	0.2749	0.0159	0.8414	0.1097

Tab. 5 - Holistic index obtained for the five considered locations as a result of the proposed Multi-Criteria Decision Model (source (Oliva et al., 2022)).

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KEYWORDS

COVID-19; Resource Allocation; Residential Area Identification; Multi-Criteria Decision-Making; · Incomplete Analytic Hierarchy Process

ABSTRACT

The COVID-19 pandemic has had an unprecedented impact on various aspects of our lives, including education, work dynamics, and social interactions. Dealing with the provision of building utilities in such circumstances has become a formidable challenge. During lockdowns, it becomes crucial to allocate resources strategically, giving priority to residential areas over commercial and financial districts based on population density. Identifying residential areas is of utmost importance not only for effective emergency response during natural disasters but also for ensuring fair distribution of electricity and gas when resources are scarce. However, accurately delineating residential zones is challenging due to the intricate nature of urban landscapes.

This paper aims to discuss a comprehensive indicator that utilizes open-source intelligence and incorporates a multi-criteria decision-making framework to assess the likelihood of an area being residential. This indicator will greatly assist in optimizing resource allocation for power, gas, and water distribution. To demonstrate the effectiveness of the proposed approach, a case study conducted in Nicosia, Cyprus, is presented.

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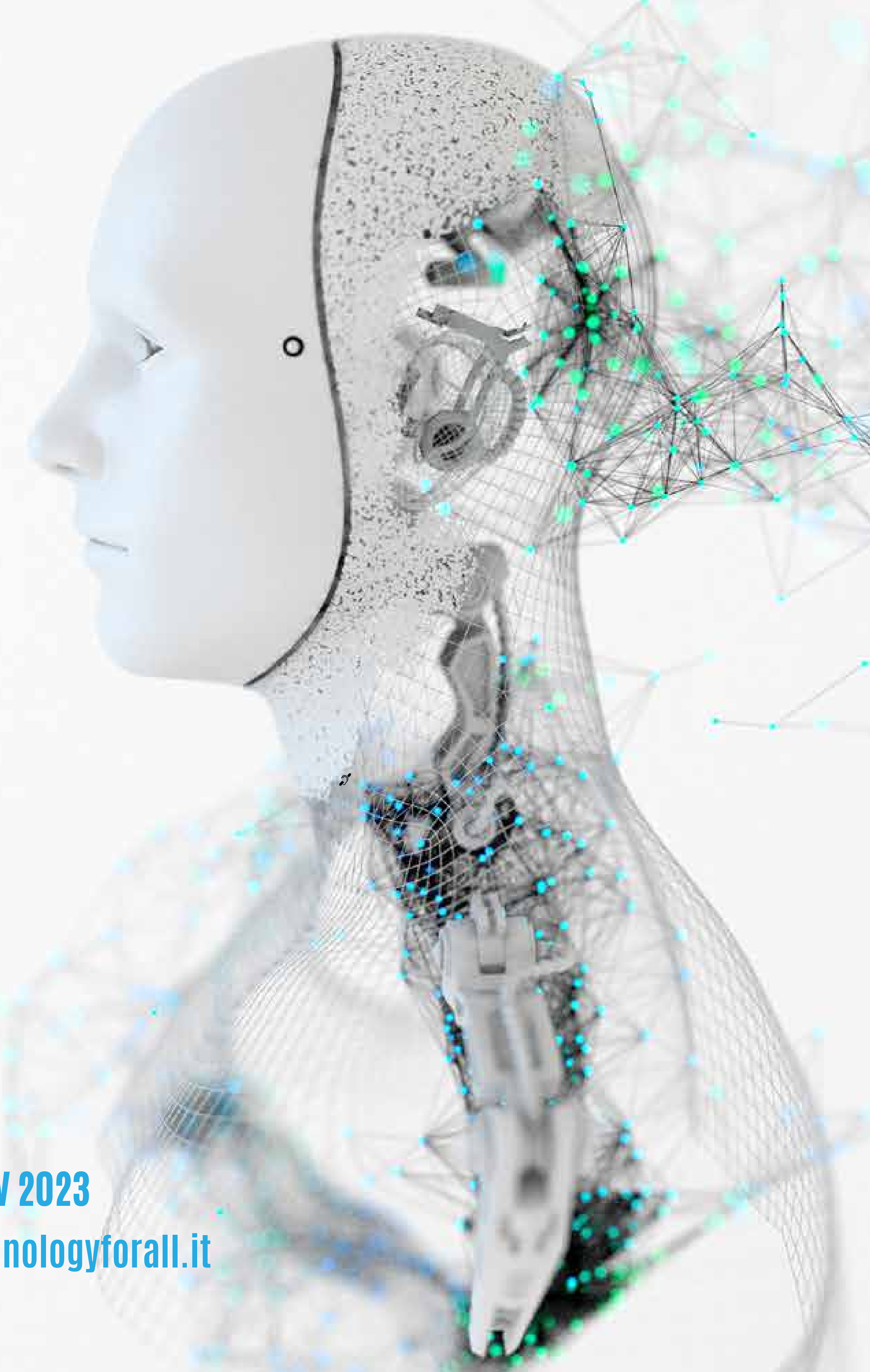

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