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A European household waste management approach: Intelligently clean Ukraine

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ABSTRACT

The European-wide environmental obstacles of inefficient and unsustainable recycling systems and flows constrain household waste (HW) management, endangering the circular economy. The European 2020 strategy and ongoing environmental disasters indicate the ineffectiveness of the current HW sustainability practices. This paper introduces an artificial intelligence (AI) approach for calculating urban residual waste, based on its generation level. It reforms the current diverse and high discrepancy levels of HW residual for EU-countries and Ukraine. Adopting a k-means clustering method with a multi-criteria taxonomic development level index (TIDL), it produces uniform clusters with higher accuracy and manageability. Findings discover and remedy opaque managerial practices, enabling sustainable and environment-friendly development at national and regional levels for EU-countries. Results reveal an increased number of clusters in crisis, contributing to a methodological reference for environmental planning. In conclusion, this AI approach could have a European-wide impact on sustainable economic value-chain, converging toward an eco-friendly economy.

1. Introduction

There is growing global concern for sustainable household waste (HW) management. HW management is categorized as a leading indicator of European environmental policy and Europe 2020 strategy (Schanes et al., 2018; Wang et al., 2018; Ponis et al., 2017). This paper contributes to the research domain of waste management by calculating the residual waste value in order to form sustainable clusters, which are of particular environmental importance. The EU highlights HW prevention as an integral part of the Commissions' new circular economy package to stimulate Europe's transition toward sustainable development and global competitiveness (EU, 2015a). Historically, international benchmarking research conducted on waste management systems in Central and Eastern European Countries (CEEC) revealed that the largest category of waste composition is residual waste (Gellynck et al., 2011). Unfortunately, these European-wide endeavours emphasize the magnitude of the problem, especially in Ukraine. Hogg and Vergunst (2017a, 2017b) confirm that an effective HW management system in CEEC should cover all waste flows. In addition, lack of urban HW recycling systems leads to the loss of millions of tons of resource materials that could potentially enter the circular economy (Pieroni et al., 2019). The development of separate systems for collecting and recycling waste is an integral part of improving the use of natural resources and transitioning to a sustainable economy (Melnyk et al., 2014). This resource-intensive process is particularly large and significant in Ukraine. However, lack of adequate response to environmental problems reveals the necessity of further scholarly research and analysis. The main difference between HW management in Ukraine and other European countries lies in the large volumes of waste generation and the lack of recycling infrastructure (Mesko and Dimitrijević, 2011). In contrast, the availability of recycling infrastructure is an indispensable feature of all EU countries (Ponis et al., 2017). This unsustainable HW supply chain diversion generates enormous amounts of waste in the country in the following ways: i) accumulation of considerable volumes of energy resources; ii) unrestrained distribution of all waste streams; and, iii) lack of systematic collection and circulation of household material. High levels of general waste generation and their low recycling rate have led to significant volumes of HW in the Ukrainian industrial and urban sectors, resulting in only a small part of HW being used as secondary raw resources, while the rest falls into landfills (Makarenko and Budak, 2017).

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In general, the HW-management system in Ukraine is characterized by the following trends: i) negative urban accumulation dynamics of large HW; ii) improper disposal and recycling practices, which affect environmental health; iii) detrimental approaches to household managerial policies; and, iv) bureaucratic practices that do not promote recycling and use of secondary raw material. As a result, significant volumes of HW and lack of effective administrative measures deepen the national environmental and socioeconomic crisis (Sotamenou et al., 2019). Reflecting on environmental studies of regional sustainability planning (Papagiannis et al., 2020) and hydro-economic imbalances in Ukraine, it is clear that trivial distribution of public funding potentially creates ecological disasters, especially for water supply networks (Papagiannis et al., 2018). As a result, the current situation requires the design and implementation of a nationwide, and potentially a European-wide, sustainable managerial plan relating to waste prevention, collection, recycling, utilization, neutralization, and environmentally safe disposal (Di Nola et al., 2018). This should be an urgent priority for the formation of an integrated HW-management system (Hogg and Vergunst, 2017a, 2017b).

In Ukraine, there are about 500 districts accumulating about 11 million tons of waste (The National Waste Management Strategy in Ukraine until 2030, 2017). The average annual rate of HW generation in Ukraine is 250–300 kg per capita and tends to increase. The dominant approach to HW management is removal and disposal in landfills and garbage dumps (Márquez et al., 2008). In 2016, only 5.8% of the generated HW was recycled, including 2.71% (1.3 million cubic meters) that was utilized (burned), 3.09% (1.53 million cubic meters) that was directed to other waste recycling complexes, and about 0.003% (2000 cubic meters) that was composted. The rest (about 94%) was buried in landfills. Additionally, the total number of HW dumps in Ukraine in 2016 was 5470, of which 305 (5.6%) were overloaded, and 1646 units (30%) did not meet environmental safety standards (The National Waste Management Strategy in Ukraine until 2030, 2017). Finally, more than 99% of Ukraine's functional landfills are falling behind EU requirements (Council Directive, 1999/31/EC of April 26, 1999 on the landfill of waste). The absence of meticulous monitoring and lack of efficient urban HW-management systems results in the annual formation of more than 27,000 unauthorized waste dumps. To be precise, out of the 1551 landfills requiring environmental certification in 2016, only 380 (21%) were actually certified in 2018.

The aim of our study is to provide an intelligent urban clustering approach to HW management in the EU and Ukraine. We present an intelligent methodology for aligning Ukrainian policies and practices to current EU environmental strategy (Communication from the Commission. A Sustainable Europe for a Better World: A European Union Strategy for Sustainable Development, 2001; EU, 2015a; Papagiannis et al., 2018). Our approach overcomes the accumulated HW obstacles by employing the k-means TIDL (taxonomic index of territory development level) model for proactive environmental threat prevention (Papagiannis et al., 2020).

Our first research objective is to identify the remaining (residual) HW that is idle and, thus, causing serious environmental issues. Our second objective is to review and optimize the existing clustering approaches and then provide a k-means clustering solution of residual waste zones using a TIDL-modified indicator. Our final objective is to associate the resulting EU-Ukraine clusters and contribute to a European-wide HW solution.

Findings reveal that the results could form the research basis for an integrated EU-Ukraine household developmental strategy. At the micro-level, we discovered the following: i) insufficient funding; ii) a lack of modern technological applications; and, iii) vague intentions to eliminate unauthorized landfills. At the macro-level, we discovered the following: i) an unsustainable HW-management system in Ukraine; ii) a Ukrainian system that prohibits the organization of green waste recycling; and, iii) incohesive European-wide environmental reporting practices. At the micro-level, findings reflect the poor ecological profile of Ukraine. Regrettably, at the macro-level, they also reflect controversial European HW-management practices, where EU policymakers plan and develop sustainability policies on the basis of less-than-optimal HW-modelling approaches. As a result, the proposed intelligent k-means clustering could guide methodological environmental auditing, planning, and forecasting.

2. Literature review and research hypotheses

According to Thomas et al. (2010), the construction and development of an EU regulatory framework for waste management policy should be based on a comprehensive waste management methodology. A hierarchical approach to waste management establishes concurrent priorities for technological innovation and sustainable development (Pomberger et al., 2017). Sustainable HW-modelling approaches should not be focused on reactive HW management at the landfill disposal stage, as in Ukraine, but instead should promote an integrated value-added supply chain (Mesko and Dimitrijević, 2011). The hierarchy of waste management technologies was first introduced in the Waste Framework Directive (75/442/EEC) and is currently a constituent of all major EU waste management directives. In principle, the introduction of waste technologies is based on optimal environmental approaches, taking into account both economically viable technological applications and social dynamics. However, it is also a fact that EU-certified dumpsites require a substantial investment relating to their design, construction, and operation, and, therefore, they severely affect the budget of individual enterprises and, of course, European cities (Ferrara et al., 2013).

According to Salhofer et al. (2010), preventing or minimizing HW generation ranks first in the EU's methodology for reducing waste. Reducing the amount of waste can be achieved by re-orienting production and consumption to products and packaging that lead to less waste (Martin-Rios et al., 2018). Product re-usage is the second most common method in the EU. This process is described by Al-Salem et al. (2009) and includes recycling practices (Andreoni et al., 2015). Recycling is defined as the reuse of materials without any significant redistribution (Yassin et al., 2005). It reduces HW problems because some packaging pieces are easily recyclable (Majid et al., 2018). Finally, the use of general waste material includes the separation of waste fractions with subsequent processing into commercial products, like composting, and potentially includes the use of recycled materials as raw materials (Wang et al., 2019).

In line with the above HW processing and utilization studies, Oliveira et al. (2019) focus on a mixed research methods' approach to HW management and modern artificial quantitative algorithms. According to Bolyard and Reinhart (2016), landfill waste disposal is the least acceptable process for waste management. Preliminary disposal requires preliminary waste preparation (Younes et al., 2016). Preliminary preparation includes the physical, thermal, chemical, and biological treatment of HW in order to reduce the amount and toxicity of waste directed for disposal. This practice could be adopted by Ukrainian cities in order to improve the country's ecological profile (Ruban and Rydén, 2019), as well as its environmental sustainability (Papagiannis et al., 2020). Eventually, the Ukrainian HW-management strategy should diverge from today's reactive practices and move toward the EU 2020 strategy (Fig. 1).

In contrast to European practices, the Ukrainian approach to waste management has remained a challenge since the Soviet era. Determining the structure of HW is not easy in Ukraine; however, we can categorize the HW according to their morphological composition (Kravchenko et al., 2018).

Since the beginning of the 1990s, independent Ukraine has encountered ongoing corruption in HW schemes (Schneider et al., 2010). According to Gasparėnienė et al. (2016), 80–90% of the country's HW

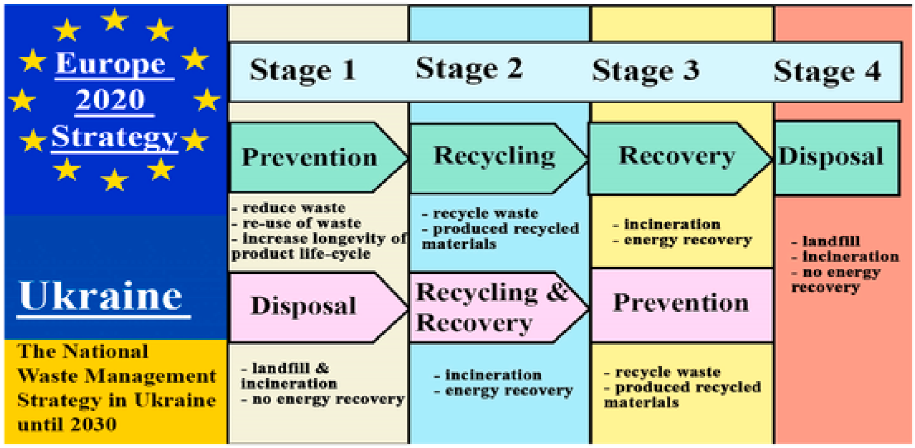

Fig. 1. HW paradigms: EU versus Ukraine.

management occurs in the shadow economy. Consequently, the most widespread method of managing HW is landfill disposal and incineration without energy recovery. In contrast to current practice, Ukrainian authorities have adopted the National Waste Management Strategy, according to which the country should eliminate their billions of tons of accumulated residual HW by 2030.

Entering the circular economic era, a quantitative model must be designed to neutralize these environmental obstacles, as well as the wide variety of other unsustainable waste processes, in both Ukraine and Europe (Perk et al., 2004; Di Nola et al., 2018). The EU 2020 strategy is far tighter and focused on sustainability. In support of such ambitious macro-level HW strategies, models based on classical clustering algorithms (Beloborodko et al., 2015) and/or hybrid AI-clustering (Niska and Serkkola, 2018) and optimization (Ayvaz-Cavdaroglu et al., 2019) should be introduced, depending on the objects of the datasets. According to Hajkowicz (2009) and Agovino et al. (2018), there is a strong and ongoing demand for waste management cluster models in Europe due to the poor performance of the existing regional models (EU, 2015a; Zhang et al., 2018). As a result, we introduce a dynamic quantitative modelling approach for European countries, focusing on Ukraine.

We consider the following hypotheses:

H1. *We could utilize, incinerate, or dispose of all urban HW in formally certified dumpsites; otherwise, HW remains abandoned in natural landfills, causing environmental harm.*

H2. *We could categorize and calculate the amount of the remaining (residual) HW according to its generation and recycle it in formally certified dumpsites or incineration plants.*

H3. *We could design an AI-HW (TIDL) clustering approach to obtain sustainable cluster values, strategically increasing environmental economics.*

To address these hypotheses, we employ a clustering methodology primarily based on the k-means analysis. The research and clustering methodology that follows reveals our systematic approach to sustainable waste management and development.

3. Methodology

Contemporary environmental methods in Ukrainian industry focus on micro-managing passive methods (Ruban and Rydén, 2019). Therefore, the production and movement of waste groundmasses enters the soil and drinking water, causing severe damage to the environment. In addition, fires from time to time occur in almost all dumpsites due to lack of environmental monitoring policies. Nevertheless, we simultaneously review EU environmental clustering approaches and country profiles in an effort to contribute to future EU-Ukraine integration. In this section, we present our research and the scientific methodologies we have employed to develop an integrated solution to the HW problem.

3.1. Research methodology

The research methodology is informed by our systematic, both qualitative and quantitative, approach and data collection. In alignment with our research aim and on the basis of our hypotheses (H1, H2, H3), we collected HW generation input data (Appendix 1) for a six-year period (2010–2016), adjusting values measured on different incineration and disposal scales in urban areas to satisfy our research aim and objectives. It is noteworthy that the primary obstacle to our research endeavour relates to the fact that regional accounting and statistical practices of urban HW in Ukraine have significant reporting gaps. Specifically, environmental reporting and normative legislation concerning HW trivially operate both in volumetric and weight categories.

We employ a descriptive methodological process map in Table 1, where we pair our research objectives with the data-analysis methodology and results in *five (v) phases*. In *phases I-III*, we micro-analyze the Ukrainian problems and EU-diversions in the field. In *phases IV-V*, we macro-analyze the wider European HW situation and discuss future conversion initiatives. Firstly, we identify the HW-management strategies in Ukraine. Secondly, we calculate the residual waste amount in the Ukrainian urban environment. Thirdly, we employ the collected data to optimize the current clustering approach. Then, we apply k-means residual waste value clustering to identify the problematic urban areas. The fourth phase is to introduce an intelligent TIDL clustering approach in order to identify the endangered European urban environments. Finally, in *phase IV*, we analyze and compare the EU-Ukraine results with contemporary research approaches.

As a result, we introduce the following five-phased scientific methodology for AI-clustering in order to re-form, step-by-step, the current environmental policies in the EU, starting with Ukraine.

3.2. Clustering methodology

3.2.1. Phase I. Problem identification in Ukraine

We reveal the HW-management strategies in Ukraine by analyzing environmental and economic parameters. In table A1 (see all tables A1-A4 in Appendix 1: Supplemental material for methodology), we observe data on the generation of HW by Ukrainian city (State Statistics Service of Ukraine, 2018). In tables A2 and A3, we correspondingly observe the amount of HW utilization by city and the amount of incinerated HW. In Table A4, we conclude with the calculated residual waste amount in the urbanized areas of Ukraine. We use this final dataset as a comparative characteristic for environmental practices of HW in Ukraine (see Table 2 and A8).

Table 1
Research and scientific methodology process map.

Phase	Research Objective	Hypotheses	Scientific Methods and Results
I	To identify and compare HW-management strategies in Ukraine; To identify household residual waste	H1 H2	Micro-level, qualitative inductive and deductive content analysis; [Section 2, 4; Fig. 1] Micro-level, quantitative analysis of official statistics for 2010–2016; statistical data analysis (descriptive; variance); [Table 2, A1-A4; A8, Fig. A1]
II	To provide k-means HW clustering of residual waste zones and situational analysis/planning	H2, H3	Micro-level k-means clustering method of vector quantization by James MacQueen, Hugo Steinhaus, Stuart Lloyd and E. W. Forgy (1967), validating clusters using the Hopkins statistic (1954); [Eqs. (1)–(4); Tables 3 and 4 A6]
III	To optimize the existing k-means clustering approach using TIDL modified indicator	H3	Micro-level k-means multi-criteria clustering method with a taxonomic method employing numeric algorithms by Hellwig (1968), W. Pluta (1976), validating clusters using the Hopkins statistic (1954); [Eq. (5); Tables 3–5, A6]
IV	To compare with European wide clustering results and identify urban areas that threaten the environment	H3	Macro-level statistical data analysis (descriptive; variance) with qualitative inductive and deductive content analysis; macro-level k-means clustering method of vector quantization by James MacQueen, Hugo Steinhaus, Stuart Lloyd and E. W. Forgy (1967), validating clusters using the Hopkins statistic (1954); [Tables 2, 6 and 7; A5, A7]
V	Integrated AI-clustering approach for EU-environmental policy, Europe 2020 strategy	H3	Macro-level k-means multi-criteria clustering method with a taxonomic method employing numeric algorithms by Hellwig (1968), W. Pluta (1976), validating clusters using the Hopkins statistic (1954); macro-level qualitative inductive and deductive content analysis: all methods from I-IV research phases; [Tables 6 and 7; general view Fig. 2]

3.2.2. Phase II. Clustering computation and situational planning and analysis in Ukraine

In *phase II,* we adopt a k-means algorithmic approach for HW clustering per local and central authorities. The selected methodology aims to verify the appropriate number of clusters for a given dataset. This is a critical methodology feature, as we seek to minimize the total quadratic deviating points from the cluster centers. Therefore, we perform a validation test, before k-means analysis, to assess the overall susceptibility of existing data to clustering tendency. Consequently, we calculate: i) Euclidean distance as a metric; ii) the number of researched clusters; and, iii) clustering quality and initial partitioning. We aim to optimize the process of the environmental formations and potentially the funding allocation. We perform a re-iterative simulation and estimate the probability that the nearest observed neighbour distances are obtained with a random distribution. Consequently, we form new clusters and we question their robustness and statistical significance. We also adopt Hopkins statistics as complementary to the k-means methodology for confirming that an exceeding value of 0.5 per grouped objects is distributed randomly and uniformly. The k-means cluster analysis method aims to divide *m* observations (from space) into *k* clusters, assigning each observation to the closest central cluster (we use the term: centroid) (Arthur and Vassilvitskii, 2006). Employing Hopkins statistical value of <0.25 at a 90% confidence level, we clearly indicate a clustering tendency for our group data (Hopkins and Skellam, 1954). It is important for the hierarchical cluster results to have a proportion of coincidences of more than 70% per group, by the k-means method, in order

Table 2
Ukraine – EU residual waste indicators.

Ukraine		EU	
City	Residual waste, %	Country	Residual waste, %
Poltava	32.7	Belgium, Bulgaria, Czechia, Denmark, Germany, Greece, Spain, France, Luxembourg, Hungary, Netherlands, Poland, Finland, Sweden, UK	0
Zaporizhzhya	41.1		
Cherkasy	42.3		
Ivano-Frankivsk	58.9		
Chernivtsi	63.7		
Khmelnitsky	64.5		
Sumy	68.4		
Kharkiv	75.4		
Volyn	76.9		
Zhytomyr	78.4	Romania	1.1
Vinnitsa	79.4	Ireland	1.5
Lviv	80.5	Austria	2.1
Rivne	80.5	Croatia	2.2
Chernihiv	83.4	Lithuania	5
Kherson	87.5	Cyprus	7.5
Ternopil	89.7	Latvia	8.3
Zakarpattya	95.3	Estonia	8.5
Kyiv	95.3	Italy	10.9
Mykolayiv	95.5	Malta	12.1
Odessa	96.2	Slovenia	16.4
Ukraine Average	*74.28*	*EU Average*	*1.9*

to overcome group formation in a random structure. Therefore, we calculate:

i) *The Euclidean distance that is used as a measure of proximity*

$$z(x,y) = x - y = \sqrt{\sum_{z=1}^{n} \left(x_z - y_z\right)^2} \tag{1}$$

where $x, y \in R^n$.

The k-means method divides *m* observations into *k* groups (or clusters) *(k ≤ m); S = {S1, S2 … Sk};* to minimize the total quadratic deviation of cluster points from the centroids of these clusters:

$$\min \left[\sum_{i=1}^{k} \sum_{x^{(j)} \in Si} x^{(j)} - Mi^2 \right] \tag{2}$$

where. $x^{(j)}, Mi \in R^n$

Mi - centroid for cluster *Si.*

ii) *The number of researched clusters*

Therefore, if the measure of proximity to the centroid is defined, then the partitioning of objects into clusters is reduced to the definition of centroids of these clusters. The *k* number of clusters is a rule-based, initial research selection. So, we calculate the initial set of *k* average (centroids) *M1, M2, … Mk* in clusters *S1, S2 … Sk*.

iii) *The clustering quality and initial partitioning*

We implement the rule-based selection of centroids that maximize the initial distances between clusters as follows. We attribute observations to those clusters whose average (centroid) is closest to them, and we assign each observation to a unique cluster, even in the multiplechoice case. Then, we re-calculate the centroid of each *i-th* cluster according to the following rule:

$$Mi = \frac{1}{Si}\sum_{x^{(j)}\in Si} x^{(j)} \tag{3}$$

Thus, based on the k-means algorithm, at each step, we re-calculate the centroid for each cluster obtained in the previous step. The algorithm stops when the *Mi* values remain unchanged:

$$Mi^{step\ t} = Mi^{step\ t+1} \tag{4}$$

Concluding the product of *phase II* is the synoptic k-means clustering table A6 (see Appendix 1) and descriptive Table 3.

3.2.3. Phase III. Maximize the k-means clustering in Ukraine

In *phase III,* we perform the following calculation steps:

Step I *Formation of an observation matrix according to* tables A.1-A.4 and equation (5). We proceed with our multifactor analysis of existing HW-management methods, formulating from waste generation factors (see table A.1) to waste disposal factors (see table A.4). We formulate according to the multidimensional objects (TIDL) method (Hellwig, 1968; Pluta, 1977), where a synthetic-value indicator performs as an equalizer of all the indexes. It clusters the elements of our input dataset, according to their Euclidean distances from the environmental standard (Etalon).

Step II *Standard deviation calculation.* We monitor the clusters for environmental threats and classify urban areas for optimal management. We commence the process of taxonomic index construction with a matrix of observations formation. This matrix forms our input dataset (see equation (5)).

Step III *Standardization and differentiation of matrix observations.* Finally, we employ the obtained taxonomic cluster results (table A.1-A.4) to analyze the HW residual utilization factors and match objects (e.g., clustering processes and HW factors) that have a large number of features.

Step IV *All variables are divided into stimulants and de-stimulants.* We define stimulants, indicated by a "+" sign, as the variables that carry a high matrix value and produce a positive HW management solution, like incineration practices or proper disposal of HW. In contrast, we define de-stimulants, indicated by a "-" sign, as the variables where the matrix value produces a less qualified or negative HW management solution, like waste generalization practices (see results in Table 5).

Step V *Calculation of the distance from individual points of factors to the* et al.*on using Euclidean formula.* Among the stimulants and de-stimulants, we calculate their Euclidean distance (see re-iteration at phase II, step I) from the Etalon (see Table 5). The Etalon is the environmental standard with the optimal value of one (1).

Step VI *Modification progress and indicator formation, based on TIDL and consequent application of k-means clustering algorithm, for clustering optimization.* Finally, to proceed to the next phase IV we perform multifactor calculations using the TIDL method, based on k-means clustering (phase II and III), achieving accurate cluster values (Grajewska, 2003). Consequently, these variables produce a qualified object, which is employed as a general clustering criterion, producing a standardization matrix. The standardization of matrix values leads to the elimination of factors measurement and aligns the matrix values. Concluding phase III (see calculation-steps I-VI), we determine the set of diagnostic variables (from tables A1 – A4, see Appendix 1) marked with the appropriate symbol X (X1, X2 … Xk) and the fulfilled information matrix of observations. The matrix is the following:

$$X = \begin{bmatrix} X1 \\ X2 \\ \dots \\ Xm \end{bmatrix} = \begin{bmatrix} X11 & X12 & \dots & X1k \\ X21 & X22 & \dots & X2k \\ \dots & \dots & \dots & \dots \\ Xm1 & Xm2 & \dots & Xmk \end{bmatrix} \tag{5}$$

where: *Xmk* – the value of the *k* diagnostic variable for the *m* object; *m* – the number of objects; *k* – number of diagnostic variables.

We used Statistica 12.0 software to perform these algorithmic steps, both on the micro level (see Tables 2–5, Appendix 1: Table A6) and on the macro level (see Tables 6 and 7 for European countries results).

3.2.4. Phase IV. Re-apply phase II k-means algorithm for European countries

Finally, we re-apply the k-means algorithm for European countries. In tandem, we employ TIDL intelligence clustering with the aim of identifying current discrepancies between European countries, focusing on Ukraine. We exhibit our results in the corresponding Table 3, Appendix 1: table A6, and Tables 6 and 7 Then, we compare the k-means results, as produced by our multi-criteria TIDL clustering approach, with the ones in existence, in Tables 3 and 7 Our statistical, qualitative inductive and deductive content analysis reveals several disastrous hidden cluster areas. Micro-level aggregate results are exhibited in Table 4's cluster-

Table 3
Statistics for AI-clustering (Ukraine).

Phase II k-means			*Phase III* intelligence TIDL		
Cluster id.	Number of cases	%	Cluster id.	Number of cases	%
1	8	40.00	1	1	5.00
2	4	20.00	2	1	5.00
3	1	5.00	3	1	5.00
4	4	20.00	4	3	15.00
5	3	15.00	5	14	70.00
Total	**20**	**100.00**	**Total**	**20**	**100.00**

Table 4
HW-management cluster-matrix[a].

Cluster identification	National, regional, municipal environmental initiatives and control			
	Stage 1. Prevention	Stage 2. Recycling	Stage 3. Recovery	Stage 4. Disposal
Cluster 1 Relatively clean urban areas	*Active*	*Active*	*Active*	*Active*
Cluster 2 Partially polluted urban areas	*Partial active*	*Partial active*	*Partial active*	*Active*
Cluster 3 "Gray zone" areas	*Inactive*	*Partial active*	*Partial active*	*Partial active*
Cluster 4 Pre-crisis cluster	*Inactive*	*Inactive*	*Partial active*	*Partial active*
Cluster 5 Crisis cluster	*Inactive*	*Inactive*	*Inactive*	*Partial active*

[a] Technically and economically feasible: *yes difficult to perform.*

Table 5
Stimulants and de-stimulants selection in TIDL index formation.

Factors	Waste generation	Utilization of wastes	Incineration of wastes	Waste disposal to the managed dumpsites	Remaining waste
Stimulant/De-stimulant	D	S	S	S	D
Etalon	−0,22	1,33	0,53	0,49	−0,21

Table 6
The results of AI-clustering (Europe).

Phase IV macro level k-means			Phase V macro level intelligence TIDL	
Case name	Final classification (cluster number)	Residual waste, (kg/per capita)	Final classification (cluster number)	Modified progress indicator (TIDL)
Austria	1	12.0000	3	0.550187
Belgium	1	0.0000	3	0.563589
Bosnia and Herzegovina	4	90.0000	5	0.462014
Bulgaria	1	0.0000	3	0.547152
Croatia	1	9.0000	3	0.544699
Cyprus	3	48.0000	4	0.531611
Czechia	1	0.0000	3	0.533926
Denmark	1	0.0000	4	0.517722
Estonia	2	32.0000	4	0.528805
Finland	1	0.0000	3	0.564262
France	1	0.0000	2	0.592084
Germany	1	0.0000	1	0.642257
Greece	1	0.0000	3	0.563328
Hungary	1	0.0000	3	0.546092
Ireland	1	9.0000	2	0.573049
Italy	3	54.0000	1	0.627470
Latvia	2	34.0000	4	0.519399
Lithuania	2	22.0000	3	0.541585
Luxembourg	1	0.0000	3	0.562847
Malta	4	72.0000	5	0.515745
Montenegro	5	119.0000	5	0.452522
Netherlands	1	0.0000	2	0.589619
Poland	1	0.0000	3	0.542819
Romania	1	3.0000	5	0.500682
Serbia	3	56.0000	5	0.469348
Slovenia	4	75.0000	4	0.524188
Spain	1	0.0000	3	0.565080
Sweden	1	0.0000	3	0.550613
UK	1	0.0000	2	0.593642

Table 7
Statistics for AI-clustering (Europe)[a].

Phase IV macro level k-means			Phase V macro level intelligence TIDL		
Cluster	Number of cases	%	Cluster	Number of cases	%
1	25	69.44	1	5	13.89
2	4	11.11	2	4	11.11
3	3	8.33	3	17	47.22
4	3	8.33	4	5	13.89
5	1	2.78	5	5	13.89
Total	**36**	**100.00**	**Total**	**36**	**100.00**

[a] We constructed our research on transparent input data from 36 countries (Europe and the EU), however, we exhibit here the most impactful clustering results. [URL] Eurostat http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_wasgen&lang=en.

matrix. Next, we proceed with the macro-level analysis, and we reperform our standard clustering approach, adjusting it to be accurate with TIDL intelligence clustering. The macro-level results analysis for leading European countries is exhibited in Tables 6 and 7

3.2.5. Phase V. Intelligent urban clustering approach for environment friendly HW planning and management

In *phase V*, based on the content analysis, we elevate this integrated EU-Ukraine research approach by introducing an intelligent k-means TIDL clustering approach, using multi-criteria factors.

In the next section, we discuss the results of this novel approach in an effort to view the HW management problem through the lens of European environmental policies and European 2020 strategic planning.

4. Results

This paper methodologically accumulates the results in *phase I* according to the identified methods of HW disposal in Ukraine. In accordance with *H1* and *H2*, we identify the amount of residual HW that is neither sorted nor utilized. Historically, even at managed dumpsites in Ukraine, HW is not fully sorted and recycled, unlike in EU countries. Therefore, the HW calculation approach varies between Ukraine and EU countries. The residual HW in Ukrainian cities is calculated by the difference between waste generation/city indicator and the sum of utilization and incineration. For example, the residual HW amount of Vinnitsa city is 1530.5 ths. t (table A8) and equals the HW generation of 1927.5 ths. t (table A1) minus the utilization of 343.4 ths. t (table A2) and the incineration of 53.6 ths. t (table A3). Although, a part of the residual HW in Ukraine is not directed to managed dumpsites (table A4 shows this exact amount of HW; e.g., in Vinnitsa it is only 105.3 ths. t). Consequently, to calculate the actual necessary treatment rate of HW in Ukraine, we use the cumulative recycling indicator as the sum of indicators in tables A2, A3, and A4 (table A8). This clear indicator exhibits the real amount of HW that requires treatment.

In contrast, EU countries' residual HW is calculated using a straightforward formula, as follows: “Residual waste” = “Waste generated” – “Waste treated” (table A5). The variations in these calculation methods are the reason for the fundamental gaps in Ukrainian HW statistics. As a result, in Table 2 we can immediately recognize that HW management policies in Ukraine are opaque and inconsistent, deviating from a coherent and uniform national threshold. Such identification gaps should be eliminated in an effort to conform to EU countries’ HW management practices.

Focusing on the percentage of residual waste/city indicator, we also find not only outliers with high values but also city indicators whose values are forming discrepancies varying from 32.7% to almost 96.2% (see also Table 2 analysis results and Fig. A1). However, equally disastrous are the European country profiles (see table A7s full analysis of results in Appendix 1), where the residual waste value in generally generated HW varies widely from 1.1% to 16.4% (see Table 2 in Appendix 1 for synoptic results). There are several factors besides the low efficiency of the HW management policy that cause these residual waste discrepancies in Ukraine. These factors are as follows: i) a post-Soviet legacy, at the state level, of low residual waste priority; ii) local authorities’ mismanagement of household waste collection and disposal; and, iii) limited funding of waste management practices. At the same time, the situation in the EU countries is much better due to a unified system of HW management within the framework of the Europe 2020 Strategy.

In accordance with *H3* at *phase II*, we employ the k-means clustering method. There is no ‘ideal’ clustering method (Sweeney and Gómez-Antonio, 2016; Arthur and Vassilvitskii, 2006). For the purposes of our study, we chose the *k-means* method as appropriate due to its sufficient calculation accuracy in economic clustering applications (Atnasova, 2017). Cluster formation results are derived when we assign *Yi* cluster numbers to *Xi* objects and select the input data according to its highest value (see Appendix 1: table A6). Therefore, the aforementioned discrepancies and their causal factors indicate the importance of residual waste zones and situational planning for an integrated EU-Ukraine clustering approach.

Finally, in *phases II and III,* we offer a synopsis of the overall statistics for k-means and intelligence k-means clustering (see Table 3). We develop the statistics in alignment with ‘The National Waste Management Strategy in Ukraine until 2030’ guidelines (Cabinet of Ministers of Ukraine, 2017), producing an HW management cluster matrix (Table 4). The matrix is subject to the following constraints: i) identification of the aforementioned critical Ukrainian parameters; ii) national- and state-level priorities per HW stage; iii) adopted artificial intelligence approach to eliminate the existing HW management infrastructure; iv) reduction of overlapping bureaucratic procedures; and, v) assurance of administrative action certification. Concluding, the statistics of *phase II* (see Table 3) are parameterized at all stages according to the cluster identification, the k-means method iteration, and the multi-level regional control.

In *Phase III* of our multi-dimensional environmental economics study, we further adjust accurate cluster values according to k-means clustering method limitations and expose undetected environmental threats according to our third hypothesis (*H3*). In Table 5, we reveal an artificial intelligence clustering, taking into account TIDL, which allows us to estimate the ad hoc average level of the achieved values, where the optimal TIDL value is one (1).

The results of Table 5 show the calculation of the distance from individual points of stimulants and de-stimulants to the etalon TIDL. Then, we calculate the total distance based on the Euclidean space and the regional development of the taxonomic index. Appendix 1: Table A6 shows the results of *phase III*-analytics per city, where stimulants and de-stimulants are able to formulate accurately parametrized and optimized clusters. As a result, these discovered waste/city discrepancies, varying from 16% for EU countries to 96% for Ukraine, reveal a 'hidden environmental bomb' (see Table 2).

The 96% for Ukraine suggests that such high micro-level discrepancies are due to a large amount of unregistered or inappropriately registered data coming from local, unauthorized landfills. At the macro level, the European waste discrepancy of 16% is equally important, as it suggests outdated environmental modelling and reporting. Therefore, 'environmentally safe' cities in clusters '1', '2', and '3' are now downgraded as 'in crisis' (clusters '4', '5'). Specifically, the city of Cherkasy is classified with the k-means standard classification in cluster '1'. When we further adjust the values with AI clustering (TIDL method), it downgrades to cluster '4'. Likewise, the city of Chernihiv downgrades from cluster '2' to cluster '4'. Additionally, we could notice that k-means cluster '5' per city percentage is 15%, and when we further calibrate these percentages with TIDL clustering, we reach 70% (Table 3). These results are altogether significantly different from the existing ones, which are based on the standard k-means approach. Therefore, we consider our AI clustering approach to be an incremental innovation that reveals hidden environmental threats due to its explicit scalable parametrization (Appendix 1: table A6). It drastically clarifies Ukrainian government data and reveals the magnitude of the HW problem, confirming international environmental reporting ('Ukraine Country Environmental Analysis', World Bank, January 2016). Our micro novelty in *phase III* allows us to design accurate, multi-criteria urban clusters in accordance with the interlinked HW stages (see Fig. 1) and further audit the implications of our AI clustering methodology at the European level. Therefore, we are not comparing Ukrainian cities with EU states' datasets, but rather revealing similar regional patterns of HW management practices.

Consequently, in *phase IV*, we discuss the accumulated micro-level results with the macro-level European ones, in accordance with the 'Europe 2020 strategy' (European Commission, 2010). The 'Residual waste' parameter produces a set of HW clusters for all European countries. According to the k-means European clustering results, we distinguish 'HW-full' and 'HW-free' countries (Table 6, *phase IV* and Appendix 1: tables A5 and A7). Analyzing the comparative characteristics of European countries, as exhibited in Appendix 1: table A7, we notice a rationale that is similar to the micro-level analysis. Specifically, in Tables 6 and 7 of *phase IV*, we notice that national HW macro clusters in the 'pre-crisis' profile include Malta, Slovenia, and Bosnia and Herzegovina (*Cluster 4* with 8.33%) and the 'crisis' profile includes Montenegro (*Cluster 5* with 2.78%).

As a result, as we enter our macro-level analysis at *phase V*, and by applying our novel TIDL clustering approach for European countries (Tables 6 and 7), we observe a significant increase in 'pre-crisis' and 'crisis' cluster profiles. The 'pre-crisis' *Cluster 4* with Cyprus, Estonia, Slovenia, Latvia, and Denmark is raised to 13.89% from its previous 8.33% (see Table 7). The 'crisis' *Cluster 5* now includes five countries instead of only one (Montenegro). These new 'crisis' zone countries are Malta, Romania, Serbia, and Bosnia and Herzegovina; and *Cluster 5* receives a higher percentage than before (up to 13.89% from 2.78%). Findings reveal significant variations in European HW profiles depending on the applied methodology. Certainly, AI clustering (TIDL method) seems to reveal significant sustainability downgrades.

We clearly recognize that, due to the qualitative inductive and deductive content analysis, the produced output data in iterative *phases I-IV* are significantly different both at the micro and macro levels. We identify the countries as in 'pre-crisis' or 'crisis' (*Cluster 4 and Cluster 5*) clusters with the k-means standard clustering method; then, in accordance with *H3*, we apply k-means clustering in tandem with TIDL indexing. This novelty allows us to secure an original system of multi-criteria hierarchical clusters, providing economically and environmentally accurate data that contain both stimulant and de-stimulant indicators. These indicators could actively integrate social, environmental, economic, and technical aspects, although our study primarily focuses on environmentally quantitative ones (see Fig. 2). The incremental innovation of our AI clustering approach is a sustainable integration of standard clustering methods (e.g., k-means method) with multi-criteria taxonomic analysis methods (e.g., TIDL). It enables simultaneous intel-

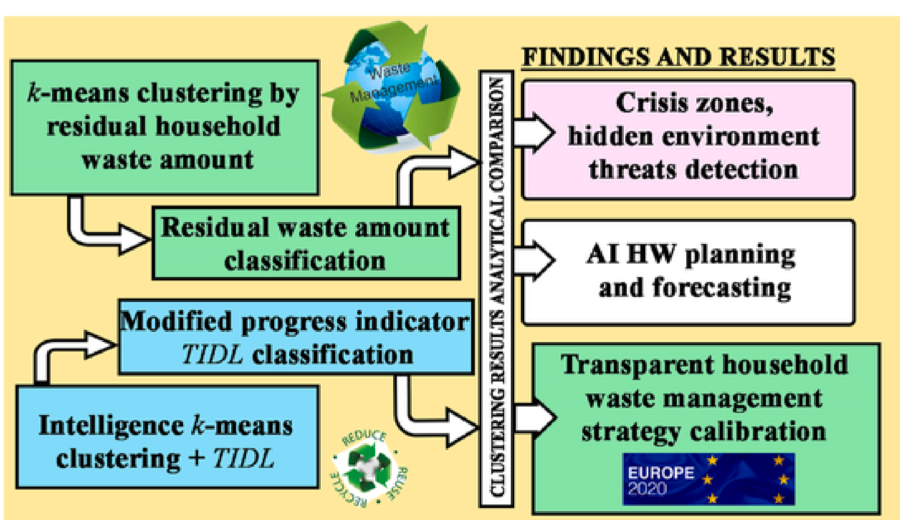

Fig. 2. Intelligent clustering findings and results.

ligent clustering, which compensates for potential gaps in standard clustering methods.

Nevertheless, there are some study limitations in relation to the following: i) initial cluster formation, which is based on existing clusters distributed according to Euclidian space; ii) k-means algorithm's random selection of clusters; iii) k-means algorithm's adoption of objects belonging to different clusters; and, iv) particular indicators demonstrating different aspects of the HW issues (see Appendix 1: tables A1-4 and A8). Therefore, particular HW indicators and algorithmic approaches could be further discussed in future studies.

In conclusion, our clustering approach increases the accuracy of the HW data categorization and analysis and clearly contributes to integrated EU-Ukraine planning by revealing similar environmental trends. Current obsolete reporting practices are fostering environmental threats, which in the case of Ukraine, are internationally confirmed. Overall, we believe that the findings of this study provide an impactful contribution for Ukraine and EU countries in the area of HW modelling, allowing us to achieve higher accuracy and environmental integration.

5. Conclusions

This study's contributions are twofold. First, it proposes an alternative solution to the European HW problem. In the absence of European AI clustering policies, our multi-criteria assessment of HW contributes to an EU country's national policymaking (see Tables 6 and 7). Considering several environmentally impactful indicators of TIDL classification, only 5% of extant clusters are signaled as clean zones, as their HW residual levels are raising to 70% from 15% today. Therefore, study findings merit an eco-friendly economic integration between the EU and Ukraine.

Second, it informs policymakers about particularly opaque HW practices, as it reveals a number of downgraded environmental clusters from clean zone clusters to crisis zone clusters. Consequently, it carries indicative evidence that current national and, to a lesser extent, European hierarchical approaches to HW problems are ineffective, revealing the need for HW waste reformation and optimal HW governance.

According to this study's results in Tables 6 and 7, these innovative approaches should focus more on the environmental indicators during the conception and design phase of a product. In addition, the production of environment-friendly products using recycled materials could preempt current European-wide residual HW discrepancy levels. As a result, in the economic value chain, stakeholders will be able to preserve energy resources and recycle at the disposal phase. It is also apparent from this study's results that we need a proactive rather than a reactive HW governance approach that abstains from the perpetuation of current diverse findings. As European countries are rapidly increasing their HW volumes, the proposed environmental cluster centers (Appendix 1: fig. A2) facilitate the progression of similar sustainability-focused studies. Its algorithmic optimization could stimulate mutual developmental alliances that promote European regional economics and sustainable cooperation. Specifically, in *phase II,* the k-means method could initiate a dynamic discussion of waste clustering issues concerning the following: i) a global minimum of the total quadratic deviation and not just the local minimum; ii) selection of the optimal initial cluster centers; and, iii) initial cluster number agreement. Additionally, this study facilitates European-wide policymaking, as it allows multiple algorithmic executions with different cluster centers and a minimum error value.

In addition, *in phase III*, we engage a multi-criteria k-means clustering according to the TIDL index, providing a macro-level cluster formation (*phases IV and V)*. The intelligent rule application and hierarchical scalable principles per HW stage innovatively enables EU policymakers to engage in proactive decision-making. The multi-dimensional TIDL clustering results facilitate environmental auditing, transparent governance, and sustainable development.

In conclusion, European policymakers should further emphasize environment-friendly practices. Future research should extend to European-wide HW policies and multi-indicator planning, as our micro and macro findings reveal a significant deviation from objective sustainability reporting.

Author statement

Fragkoulis Papagiannis: Conceptualization, Methodology, Writing-Original draft preparation, Supervision. **Gazzola Patrizia:** Writing- Reviewing and Editing, Investigation. **Olena Burak:** Conceptualization, Investigation, Software, Validation. **Ilya Pokutsa:** Methodology, Data Curation, Writing-Original draft preparation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.113015.

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