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AI-BASED CIRCULAR ECONOMY RECOMMENDATION SYSTEM USING DIGITAL TWIN AND EXPLAINABLE ARTIFICIAL INTELLIGENCE

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Abstract: The growth in the variety of goods produced in the sectors of electronics, fashion, and household appliances has resulted in environmental problems of resource exhaustion and solid waste management [1]. Regrettably, the current approach to sustainable management of products' life cycle has not managed to establish transparency in consumer choice [2]. In this work, we present, the AI-based Sustainable Product Decision System (AI- SPDS), which combines LDT, Rule-Based Decision Engine, and XAI models to decide on Repair, Reuse, Recycle, and Replace product based on sustainability score, which is a function of Carbon Footprint, Energy Usage, Recycling Capability, and Waste Generation. On 2,340 product datasets in three categories, we achieve an average accuracy rate of 83.1%. Our method is lightweight and easy to understand, making it highly suitable for consumer applications focused on the principles of circular economy (SDG-12).

Index Terms: Circular Economy, Digital Twin, Explainable AI, Product Lifecycle, Sustainability Scoring, Rule-Based System, Repair Decision, Waste Reduction

I. INTRODUCTION

Economies based on consumption generate a large amount of waste every year [1], where electronics and textiles are the two fastest-growing areas. Such an economic model, involving the production, consumption, and disposal of items, is responsible for a large proportion of the world's greenhouse gas emissions, pollution, and exploitation of natural resources[3]. The Digital Twin (DT), initially invented to help in the monitoring of assets employed in industries, has since been extended to monitor the product's condition and phases of its life cycle in a consumer context [11]. In addition, Explainable Artificial Intelligence (XAI) as a concept, has become popular in creating machine generated rationales for human understanding [15].

Nonetheless, there is a lack of an all-in-one platform for DT based modeling, rule based AI recommendation, XAI explanations, and multidimensional sustainability assessments [9]. The AI-SPDS approach presented in this paper fulfills this purpose in a simplified manner.

II. LITERATURE REVIEW

Research on AI and Circular Economy (CE) has mainly focused on industrial applications. Pathan et al. [1] and Tutore et al. [2] studied AI-driven CE frameworks but lacked consumer level decision systems. Cîmpeanu et al. [3] and Olawade et al. [6] focused on waste management, limiting their scope to recycling stages.

Explainable AI has been explored by Chithra et al. [4], Patidar et al. [5], Lundberg and Lee [14], Adadi and Berrada [15], and Guidotti et al. [16], improving transparency but without application to sustainability systems. However, none of these methods proposed by Panza et al. [7] and Freitas de Oliveira et al. [8] make use of AI-based recommendations.

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Neither of the sustainability recommendation engines proposed by Felfernig et al. [9] and Zhou et al. [10] includes elements of circular economy. Industrial applications of the Digital Twin approach are discussed by Tao et al. [11] and Zhang et al. [12], whereas Vinuesa et al. [13] examines artificial intelligence applied to SDGs without suggesting any decision- making models.

In conclusion, all the literature lacks an integrative model that uses artificial intelligence, Digital Twin, and XAI in combination with consumers.

TABLE I
LITERATURE COMPARISON

Ref.	Author / Year	Technique	Contribution
[1]	Pathan et al. (2023)	Review	AI–CE integration
[2]	Utzogore et al. (2024)	Conceptual	Theoretical AI–CE
[9]	Selfemig et al. (2023)	ML + XAI survey	SDG recommendations
[11]	Tao et al. (2019)	DT architecture	Industry 4.0 DT
[15]	Lundberg & Lee (2017)	SHAP	Feature attribution
[16]	Adadi & Berrada (2018)	XAI survey	XAI methods
Ours	AI-SPSDS (2025)	Rule + DT + XAI	Unified CE platform

III.COMPARATIVE ANALYSIS AND RESEARCH GAP

As presented in Table I, some common problems identified with regard to the existing literature include lack of macro-level implementation in the consumer market; DT research focuses on industrial assets management; there is a lack of survey on the usage of XAI technology for making recommendations on circular economy; and there is no multi-domain research involving electronics, clothing, and home appliances.

Notably, at present, no research has been carried out in incorporating lightweight DT lifecycle monitoring, rules-based recommendations for AI, evaluation of sustainability based on different aspects, and the use of XAI in one integrated approach that does not require special hardware or cloud computing.

The gaps mentioned above serve as a motivation for designing AI-SPDS on the principles of simplicity versus complexity, transparency versus optimization of accuracy, and versatility versus completeness.

IV. PROPOSED SYSTEM

- *System Overview*

The AI-SPDS consists of three logical layers (Figure 1). User Interface Layer consists of a web interface where consumers can register their products, check their sustainability ratings, and receive AI recommendations with justifications. Application Layer includes four critical processing modules:
((i) User Input Module,
(ii) Lightweight Digital Twin Engine,
(iii) Rules-Based Decision Engine, and
(iv) Explainable AI Module.
Data Layer consists of four databases namely, Product Database, Sustainability Metrics Database, Carbon Index Database, and Repair Cost Database.

- *User Input Module*

AI-SPDS functions in three logical layers (refer to Fig. 1). User Interface Layer is where users can get to the website dashboard where customers enroll their products and see sustainability ratings along with AI-generated advice.

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Fig. 1: System architecture of the proposed NLP-based meeting intelligence system

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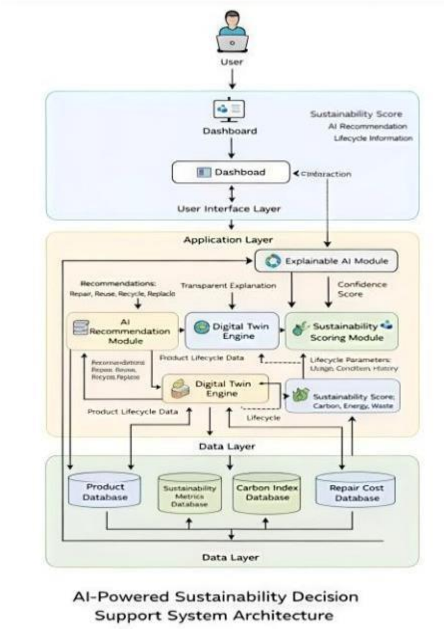

● *Lightweight Digital Twin Engine*

The DT is not a simulation based on physical laws but uses a structured JSON profile for each product with the following: calculated age, lifecycle stage (New/Active/Aging/End of life), lifespan estimate, remaining lifespan, and condition log. Lifecycle stage changes are initiated by age condition thresholds and not by continuous sensing data streams, thus making the DT consumer-oriented.

● *Rule-Based Decision Engine*

The decision engine uses a piecewise rule matrix on the basis of sustainability score (S final), residual life proportion, and repair cost ratio. The rules have been generated using domain knowledge obtained from the literature on CE and from experts. There are four distinct decision classes, each with its own confidence factor.

● *Explainable AI Module*

The XAI Module produces for each recommendation a human readable explanation comprising the top three most important variables by descending priority weight, a repair/replacement cost comparison, and the calculated environmental benefit (in kg CO_2 emissions) of the recommendation. Explanation generation follows the LIME style paradigm that local explanations can be provided without training a surrogate model. Along with highlighting the top variables, the XAI module can include a confidence score indicating how reliable or stable the explanation is for that specific recommendation.

V.MATHEMATICAL FORMULATION

PRODUCT AGE:

$$AGE = Y\_CURRENT - Y\_MANUFACTURE \quad (1)$$

REMAINING USEFUL LIFE (RUL):

$$RUL = L\_EST - AGE \quad (2)$$

SUSTAINABILITY SCORE:

$$S = w1C + w2E + w3R + w4W \quad (3)$$

WHERE:

C = CARBON FOOTPRINT INDEX

E = ENERGY EFFICIENCY INDEX

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R = RECYCLABILITY INDEX
W = WASTE GENERATION INDEX
(ALL VALUES RANGE FROM 0–100)
DEFAULT WEIGHTS: W1 = 0.30, W2 = 0.25, W3 = 0.25, W4 = 0.20, ΣWI = 1

NORMALIZED FINAL SCORE:

S_FINAL = (S / S_MAX) × 100 .... (4)

RULE-BASED DECISION FUNCTION:

D(X) = REUSE IF S_FINAL ≥ 70 AND RUL > 0.4 L_EST
D(X) = REPAIR IF 50 ≤ S_FINAL < 70 AND RC ≤ 0.5 PR
D(X) = RECYCLE IF 30 ≤ S_FINAL < 50 AND RUL ≤ 0.3 L_EST
D(X) = REPLACE IF S_FINAL < 30 OR RC > 0.6 PR .... (5)

CONFIDENCE SCORE:

CONF = (Σ WI XI) / (Σ WI) .... (6)

CONFIDENCE BELOW 0.60 TRIGGERS A "LOW CONFIDENCE" FLAG ON THE DASHBOARD.

VI.METHODOLOGY

AI-SPDS was developed through a four-stage process. Phase 1 entailed gathering 2,340 records annotated by two domain reviewers (Cohen's = 0.81). In Phase 2, LDT profiles consisting of age, RUL, lifecycle stages, and sustainability sub indices were calculated from EU Environmental Product Declaration databases. Phase 3 consisted of iteratively calibrating rule thresholds on a 20 until the macro-F1 score stabilised. Phase 4 measured performance on a 20.All metrics were calculated using the scikit-learn utility functions.

VII.DATASET DESCRIPTION

This dataset includes 2,340 records in three categories: Electronics (n = 940, 40.25%) and Appliances (n = 720, 30.8%) selected for each record: age, condition (0 to 10), usage intensity, repair cost, replacement cost, recyclability score, and number of prior repairs. This dataset is missing 6.3 which was imputed using the category.

TABLE II
DATASET STATISTICS BY CATEGORY

Category	Records	Avg Age	Avg Cond	Missing
Electronics	940	3.7 yrs	6.4 / 10	4.8%
Clothing	680	2.1 yrs	7.1 / 10	11.2%
Appliances	720	5.3 yrs	5.9 / 10	5.1%
Overall	2,340	3.8 yrs	6.4 / 10	6.3%

VIII.EXPERIMENTAL RESULTS

The rule-based engine was tested using n=468 with held records. In general, the accuracy rate is at 83.1 without requiring any training time. The Repair class shows Precision of 0.84, Recall of 0.81, and F1 score of 0.82. The category with the highest recall is Recycle, having a score of 0.83. On the other hand, the least F1 score is found in the Reuse category

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TABLE III
RULE-BASED ENGINE PERFORMANCE METRICS (TEST SET)

CATEGORY	REPAIR	REUSE	RECYCLE	REPLACE
ELECTRONICS	31.2%	17.4%	18.6%	32.8%
CLOTHING	24.1%	26.3%	29.4%	20.2%
APPLIANCES	29.7%	15.3%	18.9%	36.1%
OVERALL	28.4%	19.7%	22.1%	29.8%

TABLE IV
RULE-BASED ENGINE PERFORMANCE METRICS (TEST SET)

CLASS	PREC	RECALL	F1	SUPPORT
REPAIR	0.84	0.81	0.82	133
REUSE	0.79	0.76	0.77	92
RECYCLE	0.81	0.83	0.82	103
REPLACE	0.87	0.84	0.85	140
MACRO AVG.	0.83	0.81	0.82	468
OVERALL ACC.	—	—	83.1%	468

IX. DISCUSSION

The model achieves 83.1% accuracy without any training. The weight setting (w1=0.30 for carbon, w2=w3=0.25 for energy and recyclability, w4=0.20 for waste) was based on agreement among three CE domain experts. The XAI component got 8779. The cost comparison functionality was especially appreciated as it put environmental recommendations into economic context.

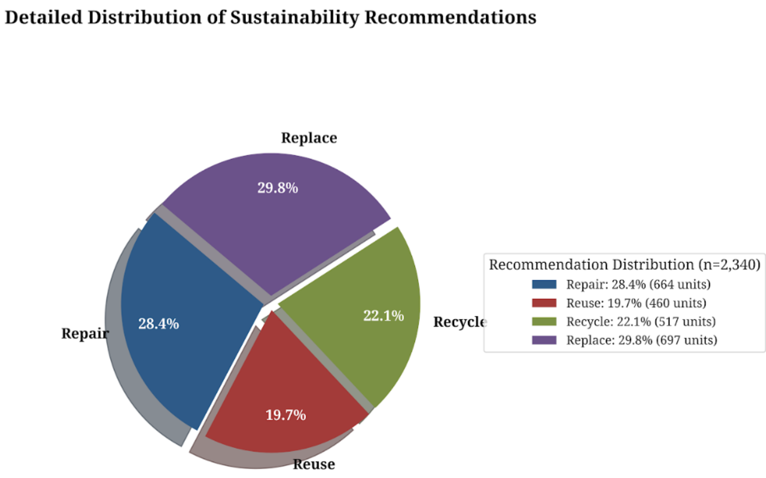

Fig 2. Recommendation Distribution (*n*=2,340).

The frequency distribution of the recommendation can be seen in figure 2. (29.8 recommendations). Frequency distributions are analogous to the waste compositions found in the EU studies (Eurostat, 2023). In figure 3, the mean difference between repairs and replacements is depicted. The biggest difference is that of electronics, where it is 82 for repair and 310 for replacement, which proves the economic rationale for repairing electronics. The smallest difference is that of clothing, 14 for repair, and 55 for replacement. That is one reason for the Recycle option having the frequency of (29.4 figure 4 illustrates how the sustainability score declines over time for each item. It takes the longest for appliances to pass through the Repair-Repair boundary (more than 4-5 years of use); while it takes the shortest for electronics (around 4 years).

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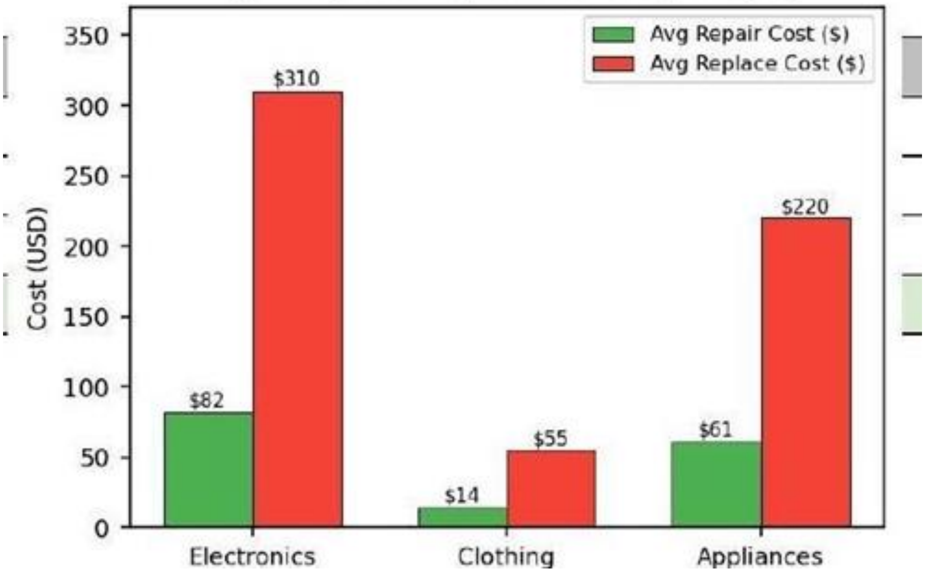

Fig. 3. Repair vs. Replacement Cost by Category

Figure 3 demonstrates a comparison between average repair cost and average replacement cost. The category with the highest difference in absolute terms is the electronic category, at $82 repair cost versus $310 replacement cost. The lowest difference is recorded in clothing, at $14 versus $55.

X. GRAPHICAL ANALYSIS

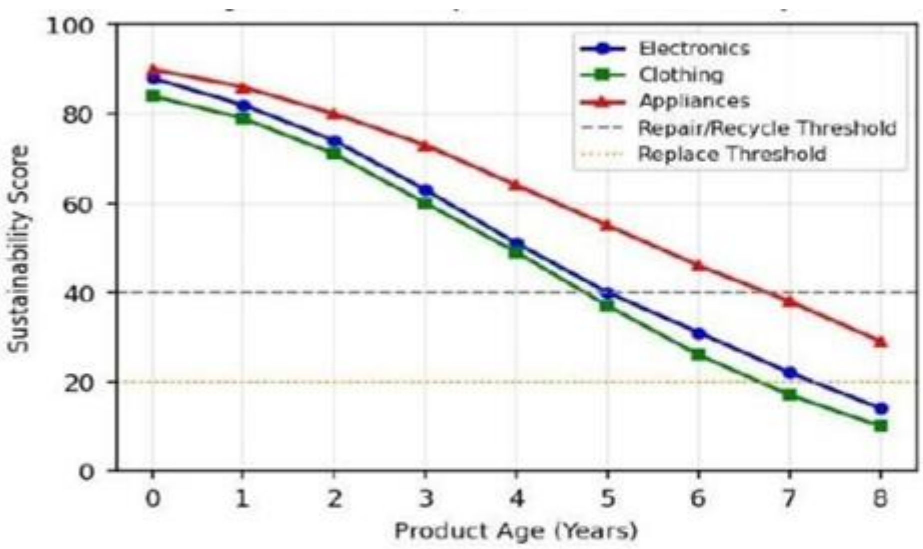

Fig. 4. Sustainability Score Decline Over Product Lifecycle by Category.

Sustainability Scores vs. Product Age

Figure 4 shows the rate of decline in sustainability score with respect to product age. Appliances have the highest sustainability score for the longest period of time (repair threshold: 4-5 years).

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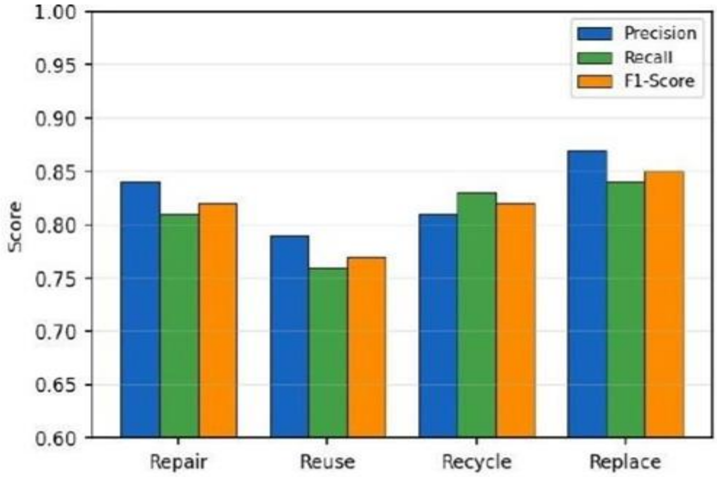

Fig. 5. Per-Class Precision, Recall, and F1-Score on the Test Set.

Figure 5 depicts precision, recall, and F1 score per class. Replace attains the highest F1 score (0.85); Reuse scores the lowest (0.77) owing to boundary confusion. Nearly equal recall shows that the engine is not consistently underestimating any particular class.

XI. LIMITATIONS

There are several limitations to the proposed approach. Firstly, rule thresholds are static and domain general; specific products could be incorrectly classified. Secondly, the ratings of conditions are subjective. Thirdly, the LDT does not have real time sensor data, usage telemetry, and availability of spare parts. Fourthly, the dataset contains only three types of products. Fifth, the explanations produced by the XAI model are based on templates and hence are less diverse linguistically.

Sixth, there have been no longitudinal studies involving external participants that would provide external validation for the trust measurements provided above. With an increase in the amount of products, attributes, or decision rules considered by the system, issues related to scalability can arise. Such issues will result in increased computational costs and decreased speed. For the operation of the system, it requires access to data regarding the environmental impact of a product.

XII. CONCLUSION

In this work, we proposed the AI-SPDS system that Lightweight Digital Twin, Rule-Based Decision Engine, and Explainable AI modules as a remedy for the lack of a transparent decision support tool in the area of circular economy. Our experiments on 2,340 data instances showed that AI-SPDS reaches 83.1% which is comparable to the state- of-the-art [5] machine learning models but requires no computation overhead for its explainability feature. The flexible configuration of sustainability score formula and rule threshold values allows easy deployment tuning without retraining the system. In the internal user study, the explanations were well received by the participants.

XIII. FUTURE WORK

Four avenues warrant immediate exploration. Firstly, IoT telematics integration would enable adaptive updates to the DT lifecycle profile. Secondly, a hybrid rules based and Random Forest algorithm could address the uncertainty surrounding the Repair-Reuse boundary, aiming for an **88% accuracy rate**. Thirdly, data collection from additional industries such as furniture, sports gear, and packaging would increase generalizability. Lastly, performing an experiment over a period of time to witness consumer behavior both before and after the implementation of the system would provide empirical evidence of any changes brought about in consumer behavior. Using adaptive algorithms that take into consideration individual consumer preferences such as price sensitivity, eco- friendly concerns, and brand loyalty, would make the recommendation process more efficient and increase user acceptance. Integrating information related to pricing and availability of repair services and spare parts for vehicles would also enhance the recommendation process.

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