Artificial Intelligence-Powered Decisions Support System for Circular Economy Business Models

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Abstract: The circular economy (CE) is preferred to linear economy (LE) as it aims to keep resources in use for as long as possible, extracting maximum value before recovering and regenerating them. This reduces the need to extract new raw materials and reduces waste, leading to more sustainable economic growth. Contrarily, LE also known as a ”take, make, use, dispose” model, is based on resources extraction, products creation, and waste disposal, which can lead to depletion of resources, environmental degradation and several other hazards. Several barriers are delaying the switching to CE. Artificial Intelligence (AI) and emerging technologies can play significant roles in the implementation of CE. In this work, A novel AI-powered model that can serve as a Decisions Support System (DSS) for CE models is proposed and demonstrated. Product life extension is created via reuse, repair, remanufacture, recycle and cascade loop. The result of the model outperformed the LE model. The study demonstrates that technologies can enable smart monitoring, tracking, and analysis of products to support decision-making (DM). AI-powered sensors and devices can monitor the use of resources in real-time, allowing for more accurate tracking and reporting of resource use.

1 INTRODUCTION

The finite nature of our planet and its resources necessitates responsible and sustainable practices of production and consumption, as evidenced by the increasing number of environmentally conscious consumers, and government policies (Brown and Wahlers, 1998; Machnik and Królikowska-Tomczak, 2022). Unfortunately, today's economy is a take-make-dispose model where raw materials are extracted for making products and then discarded after use, hence the term ”Linear Economy” (LE) (WEF, 2014). LE is considered unsuitable for both aquatic and terrestrial environments, since it also generates plastic wastes which is projected to outweigh fishes in the ocean by 2050 (EMF, 2017). The population of the world is estimated to rise by 392% in a century (1950 and 2050). As a result, natural resource consumption is also growing with a positive correlation to country's per capita GDP(Nobre and Tavares, 2017). Furthermore, LE is disadvantageous in that it is a system where virgin materials keep entering with little or no reuse at all, thereby encouraging waste generation. It has been projected that the world's consumption of raw materials will double by 2060 (The E-waste Coalition, 2019). The yearly global Municipal Solid Waste generation currently stands at 1.3 billion tonnes approximately and it is expected to hit 2.2 billion tonnes per annum before 2025 (Hoornweg and Bhada-Tata, 2012). This will be a rise of 1.2 kg to 1.42 kg per person per day, with e-waste as a critical component.

The World Economic Forum (WEF) defines e-waste as ”anything with a plug, electric cord or battery (including electrical and electronic equipment) from toasters to toothbrushes, smartphones, fridges, laptops and LED televisions that has reached the end of its life, as well as the components that make up these end-of-life (EOL) products” (The E-waste Coalition, 2019), and it is also termed as waste electrical and electronic equipment (WEEE)[1].

In 2016, worrying 44.7 million metric tonnes of

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e-waste was disposed of globally (Baldé et al., 2017; The E-waste Coalition, 2019) which is equivalent to 4,500 times Eiffel tower weight. From this, one person throws away 61kg of e-waste everyday (Baldé et al., 2017) and only 20% recycled. E-waste only makes up 2% of solid waste streams, yet it is the fastest growing waste stream and constitute a critical 70% of the hazardous waste (The E-waste Coalition, 2019). A common smart phone could contain as high as 60 elements of the scientific periodic table and many have high chance of recoverability technically. The volume of e-waste could top 120 million tonnes annually by 2050 in the worst-case scenario, based on United Nations University (UNU) estimate. There are targets in place to minimise waste generation substantially before 2030 based on the Sustainable Developments Goals (SDGs) (Forti et al., 2020), such as the SDG 12, which is ”responsible consumption and production”. The target is to ”substantially reduce waste generation through prevention, reduction, repair, recycling, and reuse”. The **e-waste sub-indicator for SDG 12.5.1** is stated as : (Forti et al., 2020)

$$= \frac{(TotalEwaste - Recycled)}{(TotalEwaste - Generated)}$$

SDG 12.5.1 for 2019 is 17.7%, which suggests that more still need to be done to increase this rate. While business are encouraged to embrace CE practices for the benefits, there seems to be numerous barriers such as uncertainty surrounding circularity decisions. Emerging technologies such as AI which has became the buzzword of recent can be employed to address this this barriers. As part of efforts towards these goals and more, whether directly or indirectly, this paper proposes the use of cutting-edge technologies such as the Internet of Things (IoT), AI, and Machine Learning in building a Circular Economy Business Model (CEBM). This paper particularly focuses on the use of AI-powered DSS as a circular business model that aims to help businesses in making data-driven circularity decisions to achieve resource efficiency, utilisation, productivity, and business benefits. The remainder of the paper is as follows: Section 2.1 will explore the barriers and opportunities of transitioning to CE while Section 3 will present the AI-Powered DSS model including the results and discussion, before ending the paper with conclusion and recommendations in 4

2 TRANSITION TO CIRCULAR ECONOMY: THE BARRIERS AND OPPORTUNITIES

As businesses are pressured to pursue the triple bottom line (TBL) which is social, environmental and economic sustainability, there are several barriers and opportunities in doing this. In this section, the paper will first identify some of these numerous barriers and opportunities, before going on to discuss the proposed solutions.

2.1 Barriers and Challenges to Circular Economy Implementation

Researchers have identified that there are various business benefits of switching to CE. “Profitability/market share/benefit”, “cost reduction”, and “business principle/concern for environment/appreciation”, are among the top 3 benefits/drivers of CE (Agyemang et al., 2019). These and other factors are putting pressure on businesses to implement CE practices which indeed, some businesses are willing to switch but are facing challenges. “Unawareness/uncertainties”, “cost and financial constraint”, and “lack of expertise”, are among the eminent barriers/challenges in implementing CE (Agyemang et al., 2019). By grouping the barriers into TBL framework (Badhotiya et al., 2021), **social barriers** include Low demand and acceptance of remanufactured products, Lack of a standard system for data collection and performance assessment, Reluctance to replace EOF products, scepticism to the quality of refurbished and recycled products, and Lack of technical and qualified personnel on CE (Agyemang et al., 2019). Other social barriers include lack of design tools for circular business models and circular products (Agrawal et al., 2021), and associated risk in transitioning from LE to CE due to uncertainties and inherent complexities (Agyemang et al., 2019). The **economic barriers** are High upfront investment costs and long-term economic return (Kumar et al., 2019), lack of funding and tax incentives (Agrawal et al., 2021), lack of appropriate partners and complexity in supply chains (SC) (Benton et al., 2017), need for advanced technologies and facilities (Kumar et al., 2019), The **environmental barriers** include lack of incentives to promote greener activities, low-tech waste resource management systems (Cuerva et al., 2014), and lack of adequate technologies used in land-filling and disposal methods (Agrawal et al., 2021) among others.

The list of barriers goes on and concerted and multidisciplinary efforts are needed to address these challenges (Agrawal et al., 2021). Most of the barriers are linked to uncertainty in operational or strategic DM which cutting-edge technologies can play a big role in proffering solutions, especially in this AI age. For instance, the problem of "Lack of a standard system for data collection and performance assessment" (Kumar et al., 2019) can be addressed by leveraging IoT and AI for tracking, monitoring, and analysing products' performance and usage on real-time. This will then eliminate the uncertainties regarding product residual values since real-time data will be collected, stored, and processed for business and circularity decisions. It could help in deciding incentives for reverse logistics purposes and creating transparency for circular SC. While it is not the intention of this paper to address all the challenges, the paper proposes solutions to address some of these barriers via the use of industry 4.0 technologies such as AI, IoT, and machine learning (Elghaish et al., 2022). specifically, these technologies can help in tracking products in real-time, gathering data, and analysing such data on a real-time basis which could improve business value, and achieve resource efficiency and a safe environment. Technology has the capacity to pursue the various aspects of the TBL, so the next section will look at how technological potentials are available for enabling and implementing CE.

2.2 Opportunities/Enablers of Circular Economy

Though there are numerous barriers to CE implementation as identified in Section 2.1, there are also many opportunities and drivers for the implementation of CE, especially where emerging technologies can serve as enablers of CE practices to overcome the challenges (Lopes de Sousa Jabbour et al., 2018; Mboli et al., 2022; Bressanelli et al., 2018). Some of these emerging technologies will be identified in this section. In the construction sector, there have been efforts that proposed the integration of IoT and deep learning for detecting the deterioration of structural health for bridges' elements caused by environmental factors. This can extend the lifecycle of these elements in operations when dedicated early(Elghaish et al., 2021). Digital technologies could also be used for innovative business models that aim to pursue CE practices. For instance, IoT and Big Data analytics are being used by businesses to servitise business today (Bressanelli et al., 2018). As is the case with most academic work in this area, this work was conceptual, limited to the construction sector, and lacks real-time data collection which is critical for CE. The use of technologies as enablers for CE requires collection of real-time data for effective analysis and decisions making (Agrawal et al., 2021). Therefore, a framework that uses low-cost sensors in reusable products or devices to gather data was proposed in (Ramadoss et al., 2018). The framework employs AI to analyse the collected data so that reusable materials can be detected and eventually reused for other products. While this appears like a step in the right direction, it was a theoretical/conceptual discussion that lack practical implementation and evaluations. In practice though, there are companies that are making efforts towards CE implementations, though slow but still encouraging. such examples include Philips Lighting, Cisco's sports shoes, Arup's circular building, Uber, Airbnb and many other examples as highlighted in (Nobre and Tavares, 2017; Uçar et al., 2020). Another work also identified the roles of digital technologies in supporting CE, based on a literature review with 3 case studies which evaluated the relationship between CE and digital technologies. Business Model Canvas was employed for integrating R-principles such as reuse, remanufacture and recycle for that research (Uçar et al., 2020). Two roles of digital technologies were identified as:

- "Digital technologies as an enabler: how digital technologies can facilitate the development of CE and improve the collaborations between actors of its ecosystem?
- Digital technologies as trigger: how digital technologies can initiate or lead to innovation processes or outcomes or associated organisational routines and mechanisms?" (Uçar et al., 2020)

These works and others not cited here all indicated that emerging technologies can play important roles in the implementation of CE whether as an enabler or a trigger. Since the main issue starts with the LE which practices a linear SC, the first step is to create a closed-loop supply chain (CLSC) leading to CSC which is entirely different from the linear SC by employing appropriate technologies (Mboli et al., 2022). However, CLSC is not enough as it basically represents the combination of forward and reverse logistics such as movement of goods to consumers and back to the original destination. A more preferred system is the CSC which is not just about closing the loop but also considers how circular the system is, the value it creates, how resource efficient and how sustainable it is (Mboli et al., 2022; Brändström and Eriksson, 2022; de Lima et al., 2022). A CSC entails a firm reusing or repurposing products, components, or materials and returns from customer to convert same into new or refurbished products. This can either be for same usage or different usage altogether but it aims to minimise the use of raw materials and waste generation. Due to its advantage over a CLSC, it can be augured that scholars have lately raised interest in exploring CSC and its benefits especially management of uncertainties (de Lima et al., 2022).

Therefore, a novel innovative circular business model that can serve as a DSS for business is presented. The model leverages on 4 Rs (reuse, repair, remanufacture/refurbish, and recycle) which are mostly discussed in CSC literature (de Lima et al., 2022; ResCoM, 2017). The novel model also draws strength from a cascading framework presented in (Campbell-Johnston et al., 2020). Hence, the five main terms that this AI-powered model builds on are reuse, repair, remanufacture, recycle, and cascade. In practice, The work will use technology to create 5 different cycles in such a way that a product, its components, or its inherent materials will pass through based mainly on it lifecycle and use cycle and the next section will discuss how this is done.

3 THE AI-Power DSS FOR CIRCULAR ECONOMY BUSINESS MODEL

As many studies pointed out some barriers mentioned in Section 2.1, most of the barriers are either directly or indirectly linked to technology. For instance, lack of SC integration and effects of SC complexity, lack of industrial support, quality of finished products, profit and market demand level, associated uncertainty risk, lack of technical and technological capacity, cost and financial constraint, and top management resistance were pointed out in (Agyemang et al., 2019). It can be argued that a robust circular business model with real-time, tracking, monitoring and product analysis will provide the ability for businesses to make both operational and strategic data-driven decisions. Therefore, the top management will likely embrace it once decisions making becomes easier, SC visibility and transparency could also help in mitigating the SC complexities. And this could a long way in answering the challenges. Some businesses are unable to reuse materials from returned products since the status or quality of those is unknown haven been with users for sometimes. other barriers already identified from the analysis of scholars include the lack of a standard system for data collection and performance assessment and poor CE knowledge, scepticism to the quality of refurbished and recycled products, need for advancement of technology and facilities, and high cost of establishing eco-industrial chains (Badhotiya et al., 2021). Following what emerging technologies are capable of accomplishing as discussed in Section 2.2, it can be argued that this is right to explore the capability of these technologies in domains with no standard taxonomies with numerous uncertainties. Hence, this paper proposed an AI-Power DSS for CE Business Model which will be discussed in the following section.

3.1 AI-Power Decisions Support System for Circularity Decisions

This is an AI component of a CEBM as proposed in (Mboli et al., 2022) that utilises the power of AI for material circularity and business decisions. The work is a transformation of linear forward SC to a CSC via enabling technologies. Various AI types such as expert systems, rule-based systems, machine learning, deep learning, fuzzy logic systems, and so on exist, however, this work employs a hybrid AI system consisting of rule-based, machine learning, and fuzzy logic systems. There are basically five circular keywords that the model depends on, which creates five different routes for the efficient and circular flow of materials, products, and components. These fives routes are also referred to as classes in technical terms for implementation in IoT and AI-enabled circular model as depicted in 1 and discussed in the following paragraphs.

The first route is **Reuse** which is a term that covers all operations where a product is, or its components are, put back into service for a new use cycle. Components of a product can be reused in a new product as well. (ResCoM, 2017). In the context of this work, reuse (Figure 1) specifically refers to functional products/components that the first users intend to change due to other reasons other than failure. It implies the product is ready for a secondary user without any update or upgrade and can be redistributed almost immediately. The real-time data and analysis provide the firm with up-to-date status and value of the product, lowering the complexity of DM regarding the product. This enables businesses to make decisions such as the right amount of incentives, the logistics costs, and the cost of securing a secondary market with minimal or no risk.

The second route is **Repair**, which focuses on correcting "specific faults in a product to bring it back to satisfactory working condition" (ResCoM, 2017). Here, the repair route/class will normally apply to

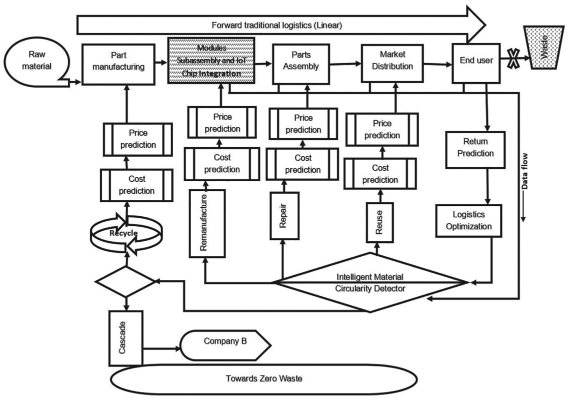

Figure 1: An Internet of Things-enabled decision support system for a CEBM. Source: (Mboli et al., 2022).

products or components that need just minor fixes to get them working again. The costs associated with this route will normally be low which the AI model can predict easily and also support DM around incentives and secondary market.

The third route is **Remanufacture** which "denotes the process of disassembly of products into components, testing and recombining those components into a product of at least original performance". (ResCoM, 2017). In most cases, the resultant new product might be given a warranty that is similar to that of an equivalent product manufactured out of all new parts but this will normally be decided by the business. Given that **Refurbishment** refers to the process of returning a product to a satisfactory working condition (Gharfalkar et al., 2016; ResCoM, 2017), this work categorises refurbishment to the same class as remanufacturing to avoid the disagreements and ambiguity between the two terms.

The fourth route is **Recycle** which is "the process that recovers material from products at the end of their lifecycle. The materials recovered feed back into the process as feedstock for the original or other purposes" (ResCoM, 2017). The focus here is on upcycling which can be described as "upgrading because the resulting outcomes still need to enter the recycling infrastructure" to create a product of higher quality or value than the original (Korley et al., 2021). The purpose here is to pursue zero waste, a CE key target, hence, its choice over downcycling. Downcycling is "recycling materials into new materials of lower performance and/or functionality." (ResCoM, 2017).

The fifth and the last route is **Cascade** "Cascade here refers to the recovery of materials which can no longer be used by the same company/industry or cannot be employed for the original purpose but can still serve another purpose whether in the same company or a different company. For instance, textile material can serve different purposes such as clothing, furniture, carpeting", etc (Mboli et al., 2022; Mishra et al., 2018).

The main aim of this novel AI-powered CE business model is to track and monitor the real-time status of products and components to make material circularity decisions based on the five routes/classes explained above, which currently do not exist. The decision is made based on real-time data on lifecycle, use cycle, usage pattern, temperature, and other factors as they contribute to the effects of wear and tear on products, components, and the inherent materials. "A lifecycle of a product starts when it is released for use after it has been (re)manufacture. It ends when it is disposed of (landfill/material recycling) or dismantled to harvest/reuse its components. The lifecycle of some (or all) of the components can continue in new products when the lifecycle of a product ends. If an essential amount of components form part of the same new product, the product lifecycle continues in that product." (ResCoM, 2017). This implies that a product will still fail and not be suitable for use once its lifecycle has elapsed though it might not have been in use from the time it was (re)manufactured. Therefore, if the lifecycle of a product and its components can be monitored, the barriers relating to scepticism on the quality of returned products as identified in Section 2.1 can be overcome. Another factor to monitor on a real-time basis is the quality of the products regarding the use cycle or mean time to failure (MTTF) cycle (Motovilov and Lutchenko, 2022). The factor is the information about how many times the product or components should be used before it fails due to wear and tear. Therefore, lifecycle depends on the duration or lifespan of a product/component which is drawn from constituting materials, MTFC is the recommended number of times used and the duration of usage minus the actual number of times and duration of usage. This leads to a third factor that needs to be monitored too and that is consumer behaviours or consumer usage patterns of a product. This also depends on the number of users per product and the season as well. With this information, the AI and IoT-backed model is able to provide insights for making decisions as will be seen later. This will also motivate businesses in implementing CE as the uncertainty barrier identified in (Badhotiya et al., 2021) is overcome. The key component of the model is performing descriptive, diagnostics, predictive, and prescriptive analytics in CEBM is the Intelligent Material Circularity Detector (IMCD) which will now be discussed in the next section.

3.1.1 Intelligent Material Circularity Detector

The IMCD is an intelligent component that works with real-time sensor data generated from CEBM. CEBM is an IoT-enabled circular business model that uses IoT chips to monitor products on a real-time basis and transmit data via WIFI. It depends on semantic technologies and an ontological model that works with reliable 5G networks for real-time products and components tracking, monitoring, and analysis. The focus of this paper is to discuss the working and benefits of IMCD, which is the re-engineered building block of CEBM. However, the full details on how CEBM work, its architecture, the experimental use case, the datasets, and more information can be found in (Mboli et al., 2022). In favour of size and to keep this work within its limits and scope, the paper will now focus on IMCD only.

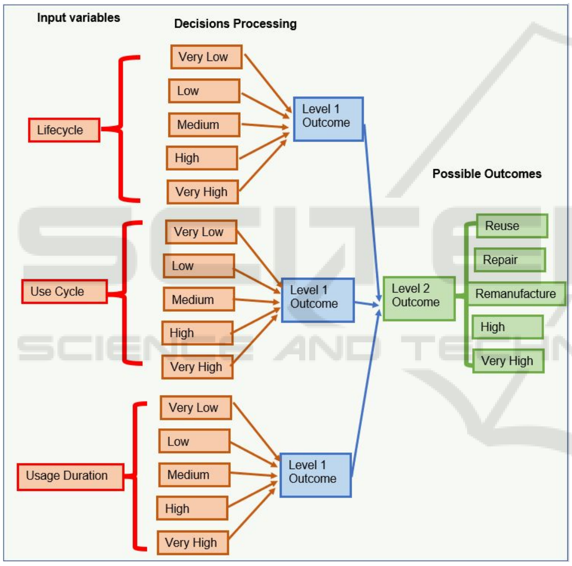

Figure 2: Intelligent Material Circularity Detector.

Data is obtained from smart products with the aid of IoT and reliable 5G networks and analysed with AI to support DM on the future flow of products. From the analysis, five outcomes referred to as routes or classes discussed earlier are possible as seen in Figure 2. Every product is monitored against functionality first, and if it is functional, re-commerce is possible without further analysis else, a component-by-component examination is necessary to detect which component has failed and that may either lead to repair, remanufacture, recycle, or cascade loop (see Figure 2). The IMCD is dependent on the principle of AI that utilises a rule-based system, fuzzy logic, machine learning, and semantics technology that support DM despite the uncertainties and ambiguities around residual values of products. Factors such as material lifecycle, product use cycle, product usage duration, temperature, and current status of the product are considered for this work. Each product is constantly and automatically monitored for reusability and failure analysis by examining its components for functionality with the IMCD. This ensures that the material stays longer in use via the 5 different routes of CEBM, thereby keeping the products, components, and inherent materials in use longer at the highest value possible. The next subsection will outline how these AI rules are developed using machine learning, fuzzy logic, and semantic web technologies.

3.1.2 Tools and Implementation

The work is implemented with Python, GraphDB, and Protegee from modeling to data collection, analysis, and visualisations. Fuzzy logic was employed due to its capability to handle uncertainties including issues of partial or incomplete data. The procedure for implementation in protegee using web ontology language (OWl) is fully explained in (Mboli et al., 2022). Python programming was chosen for its wide acceptability, compatibility, and high-level nature. Implementation using fuzzy logic follows standard procedures as recommended in (Wang and Mendel, 1992). Since the focus is to classify products, components, and materials based on lifecycle, use cycle, usage duration, temperature, and usage patterns. In python, the implementation package is called "SciKit-Fuzzy"[2] which contains default membership functions that can be 3, 5, 7, or customised functions. This provided the opportunity to transform the independent variables (properties of products, components, and materials) and the dependent variables (classes) 2 to the 7 default membership functions available in Python. So, instead of the Very Low, Low, High, Medium, and Very High, IMCD was implemented with excellent, good, decent, average, mediocre, poor, and dismal fuzzy memberships. The classes reuse, repair, remanufacture, recycle, and cascade were developed using customised membership functions and the temperature was broken into high, good, and poor with the customised membership functions as well. An example of this is shown in Figure 4 for lifecycle only though all the properties followed a similar approach. All the properties are the independent variables except the class (routes/outcomes) is the dependent variable since the purpose is to predict the class of each product, component or material based on its properties.

[2]Scikit-Fuzzy is a collection of fuzzy logic algorithms intended for use in the SciPy Stack, written in the Python computing language. https://tinyurl.com/5n7766hh

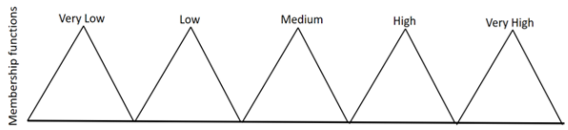

Figure 3: Initial Membership Functions for Durability.

After fuzzification, Figure 3 then became Figure 4 as implemented with SciKit-Fuzzy for convenience.

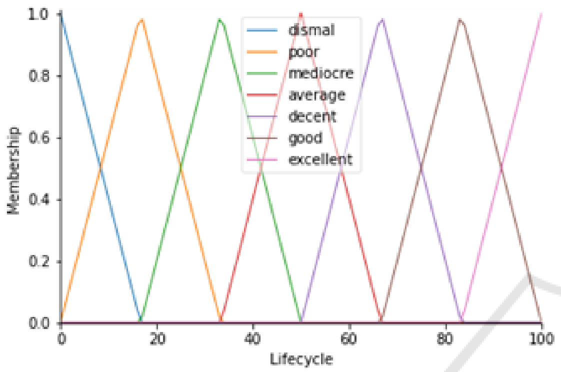

Figure 4: Fuzzy Representation of Use Lifecycle as Antecedent (Input).

3.1.3 Rules and Decisions Matrix

The seven default intervals are "dismal", "poor", "mediocre", "average", "decent", "good" and "excellent". In order to prepare the real-time datasets for modelling using a fuzzy modelling system, the following steps were adopted from (Wang and Mendel, 1992) for transforming the dependednt and independent variables to triangular fuzzy sets since it is easier to represent in embedded controllers as shown in Figure 4:

- Divides the input and output spaces of the given numerical data into fuzzy regions.
- Generates fuzzy rules from the given data.
- Assigns a degree of each of the generated rules for the purpose of resolving conflicts among the generated rules.
- Creates a combined fuzzy rule base based on both the generated rules and linguistic rules of human experts; and,
- Determines a mapping from input space to output space based on the combined fuzzy rule base using a defuzzifying procedure.

Several rules were created in line with recommendations from CE and other disciplines' domain experts (DEs) as it is an interdisciplinary work (Mboli et al., 2021). For the scope and limited space, the description of the semantic web can be found in (Mboli et al., 2022; Mboli et al., 2021) and the machine learning models used and the entire rule sets are not included here, but below is a sample of the rules is below. This is a simplified rule that depends on the current status of the product but it is just one of the many rules.

"IF lifecycle is good usecycle is excellent at room temperature THEN class is reuse"

Rule14 = ctrl.Rule(lifecycle['good'] &usecycle['excellent'],classes['Reuse'])

The implementation of these rules makes classifications of products and components possible to support businesses in DM based on the properties. The same rule is visualised in Figure 5 revealing the various conditions as membership functions and the possible outcomes when simulated with data in Python.

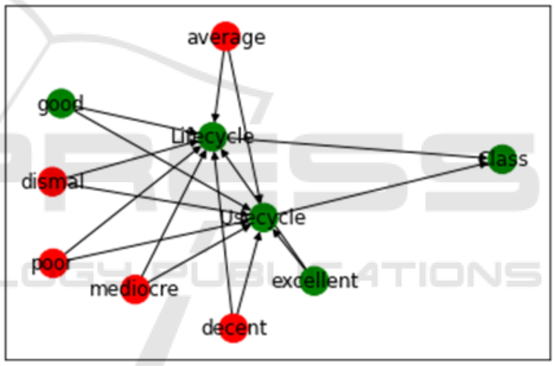

Figure 5: Visual representation of the input n-dimensional array for rule14.

3.1.4 Use Case and Description of Datasets

The datasets used in this work consist of two parts. The first part is from a company that manufactures and markets coffee machines via LE. The datapoints in this dataset include MTTF cycle, lifecycle cycle, manufacturing cost, logistics cost, etc. as described in (Mboli et al., 2022) The other part of the datasets is real-time sensor data from the IoT-enabled model. The datapoint from this part includes temperature, start time, end time, usage duration, and so on as seen in Figure 6 (Though illegible, but it is only an indication as the datasets is larger than can be included visibly here).

While it is difficult to fully describe the datasets and each datapoint here, this section only provides a brief overview of it for the benefits of understanding

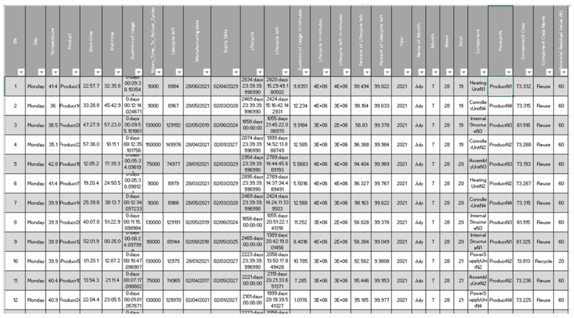

Figure 6: A snapshot of the datasets showing days, times, lifecycle etc. of products and components.

Figure 7: Use Case Overview. More at (Mboli et al., 2022).

the working of the AI-powered CE model. The company is practicing LE and exploring means of circular business model for manufacturing and marketing coffee machines. Generally, coffee machines are made of 6 different materials and 7 different components as grouped in Figure 7. Figure 7 is only for illustration and has no link with the company that provided the datasets for this work. Figure 6 It is difficult to make sense ofOR comprehend Figure 6 without analysis. This necessitated the analytical processes to draw insights from the data make data-driven decisions that are environmentally, economically, and socially sustainable.

3.1.5 Results and Discussions

Insights on the classification of products/components into the 5 classes can support a company's DM over which component or product to increase/reduce production, therefore enabling just-in-time (JIT) strategies and so on. Considering Figure 8, the majority of the components are classified into “Reuse” class, while a few fall into “Recycle” and “Repair” classes. “Cascade” and “Remanufacture” classes have the least number of components based on the datasets. This kind of information can be useful for companies that are practicing or intend to implement JIT and can even support inventory management, strategic and operational DM.

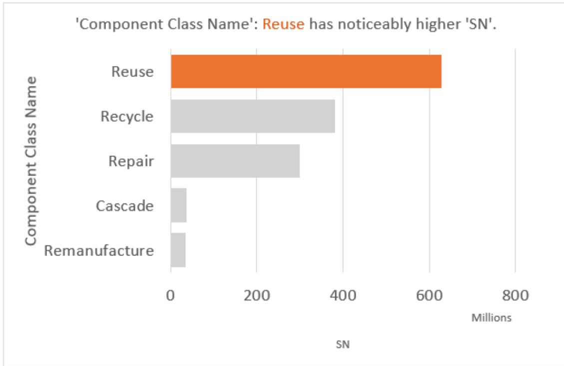

Figure 8: Components Distribution by Class showing Reuse Route with the Highest Quantity.

Similar insights from the datasets is in Figure 9 where products used by day is presented. The figure reveals that of the analysed products, more products are being used on Tuesdays than the other days with Sundays being the least. This kind of insights can inform DM for businesses to determine the days of the week that their products are being used the most, and which days they will likely experience high product failures, issues, or returns. This can support business DM toward CSC planning, return prediction, and so on.

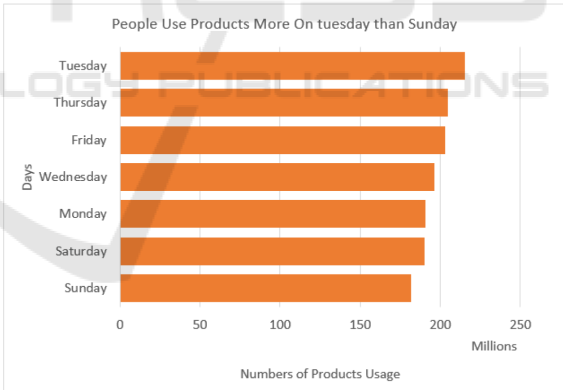

Figure 9: Products Usage Variations by Day.

Information on products' temperature variations can also suggest why and when these products may fail as seen in Figure 10. With the ability to drill down into the data, the temperature at which a product is being used can affect how long the product will last. If it is always used at an adverse temperature other than the recommended temperature, then there is a high chance that the product may not last up to its lifecycle and/or MTTF cycle.

CEBM is capable of predicting the future class of a product or its components based on real-time

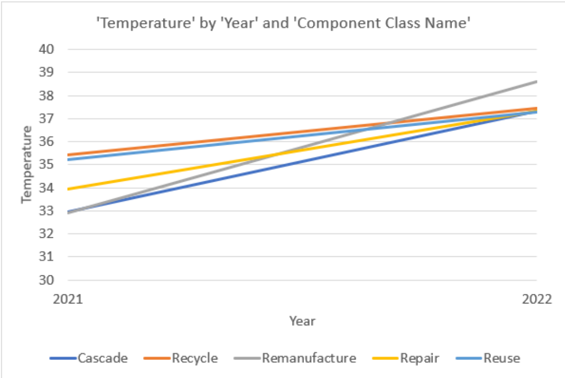

Figure 10: Temperature Distribution by classes and Years.

datasets on the properties of the products and current classes using machine learning algorithms. The simplified and summarised results of prediction is presented in Figure 11 for easy visualisation and comprehension. A similar prediction result is also possible using SPARQL Queryy as can be seen in 12 implemented in GraphDB. The presented data included class, returns on sales (ROS), use cycle, lifecycle and temperature for each product.

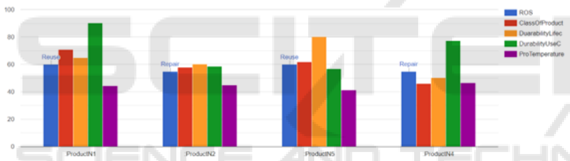

Figure 11: Interactive Products Visualization Using GraphDB.

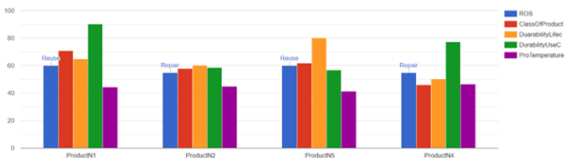

Figure 12: Product Classification from SPARQL Query.

Acquiring data is important only if value can be derived from the data, else a waste of resources and time. Therefore, this AI-Powered model was developed to help businesses in acquiring and making sense of their data for material circularity and business intelligence. Four standard types of data analytics which are descriptive, diagnostic, predictive, and prescriptive analytics as discussed in (Menezes et al., 2019) are used for this work. Descriptive analytic answers such questions as what is happening in the business? Comprehensive, accurate, and live data with effective visualisations such as Figures 8, 10, 9, 11 and 12 seen in this work can be used to answer such questions. Diagnostic analytics provide reasons to why what was discovered in the descriptive analytics stage happened. The possibility to drill down to the root causes of what is happening in the business is done at this stage to further understand the situation. It entails the ability to eliminate all confounding information using integrative dashboards, so that the issues identified, and the causes become even clearer for supporting informed DM. Predictive analytics offers answers to the question of what will probably happen if nothing is done. It investigates if business strategies have remained moderately consistent over time but now yielding different outcomes. Historical patterns and datasets from the use case are employed to predict specific outcomes using machine learning algorithms suitable for each dependent variable as was done in this work where combinations of technologies were used for various predictive analysis. Most important is what happens with the predicted results and that is prescriptive analytics, requiring DM to take action based on recommended solutions. Prescriptive analytics suggest what need to be done to mitigate the issues discovered in the first 3 stages of the analysis. At this point, recommended actions based on champion and challenger testing strategy is employed which explains why multiple strategies and techniques including DEs were used in developing the model (Menezes et al., 2019). Advanced analytical techniques could then be applied to make specific recommendations regarding products circularity and returns/values as seen in Figure 13. A comparison of the performance of the AI-powered model presented in this work and LE model shows that the novel AI circular model presented here outperformed the LE in all scenarios (see Figure 13). The scenarios presented are for reuse, repair, remanufacture and recycle. Having demonstrated how technologies can be used to provide DM support to businesses in this work, the next section will focus on conclusions, recommendations, and future research directions.

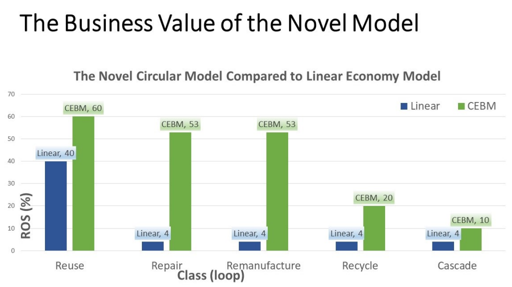

Figure 13: Model Contribution and Business value.

The ontological model was evaluated for technical compliance in OOP! scanner as presented in (Mboli et al., 2022) while the DSS was evaluated for quality of modelling and domain coverage with DEs as presented in (Mboli et al., 2021).

4 CONCLUSION AND RECOMMENDATIONS

This paper proposed an AI-powered DSS model that leverages hybrid AI concepts to enable CE principles. The results of the novel model outperformed LE as seen in Figure 13, where reuse scenario produced a ROS of 60% as against 40% of LE. This is due to the fact reuse loop has no manufacturing costs but there is optimised cost for secondary market logistics and incentives. The work provides businesses with real-time tracking, monitory and data analytics of their products which then reduces complexity due to uncertainties and supports DM. With these results, it suggests that emerging technologies can help achieve the following:

Resource efficiency and optimisation: AI algorithms are capable of optimising the use of resources in manufacturing and production processes, reducing waste and increasing efficiency. As demonstrated, reuse, repair, remanufacture, recycle and cascade were created as a means of product life extension enabled with technologies.

Predictive maintenance: With the real-time descriptive, diagnostic, predictive, and prescriptive analytics as done in this work, AI can help predict when an equipment, product or its components is likely to fail, allowing for proactive maintenance that can extend the life of these products, components or resources via re-commerce. This supports SDG 12 and will potentially contribute to the e-waste sub-indicator for SDG 12.5.1 now at 17% as discussed in Section 1.

Recycling and waste management: The model and indeed AI can be used to sort and classify waste for recycling, making it more efficient and eliminating the amount of waste sent to landfills with upcycling.

CSC management: Another critical area of CE is the circular flow of materials and products in the SC, reducing waste and making it easier to track the origin of products/materials which AI can optimally enable. This goes beyond SC visibility as this model also enabled real-time tracking, monitoring, and analysis of products, components and materials whether in transits or already in use at the users' end.

The bottlenecks encountered during this work include a lack of standard taxonomies for CE, a lack of evaluation frameworks for interdisciplinary models such as the smart AI model, a lack of data availability, and limited DEs as CE is relatively new. Therefore, future efforts in this area could be channeled toward addressing these limitations. The particular focus of this paper was on a business-only DSS where businesses are able to address uncertainties around products residual values, incentives, secondary market costs and other re-commerce-related costs before delving into CE. Therefore future research in this area should consider DSS for other SC partners so that they are also able to make informed decisions. Other areas that need to be researched include the explainability and interpretability of complex AI models such as the one presented here to encourage usability and acceptance as this was picked up by DEs during evaluations. As it is the case with many IoT and AI applications, Security and privacy issues remain a concern and were also highlighted by DEs and evaluators of this work. So this is still a challenging area that future researchers could look into. Policies around market-based incentives or finance are other aspects to consider if CE practices is to be recommended to all businesses and users.

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