Feasibility Study Analysis of Bottle Reverse Vending Machine Based on Value Engineering Concept using IoT Approach

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Abstract

In this study, waste management based on an intelligent waste management system using IoT applications is applied. Especially for plastic bottle waste, which has economic value. In this study, the authors design a DAUR machine to receive plastic bottle waste according to the user's design requirements and objectives. In addition, a simulation of investment feasibility is also carried out using system dynamics according to the Bass Diffusion Model. Two cases are simulated, according to the design alternatives made. From the simulation results, it is found that this technology will be adopted by the community quickly so that it is predicted to enter a saturation period at the end of the fourth year. In addition, the 16% increase in investment costs for machinery has resulted in a lower NPV of up to 68%. However, investment in both design alternatives is still feasible because it has an NPV value greater than zero. Analysis of the results of the sensitivity test was also carried out by the author with a variation of factor values of +20% and -20% so that 12 additional simulation cases was added. The author has also made an identical design on the prototype of the DAUR machine for easy modification, maintenance, and efficiency of manufacturing time.

Keywords
Plastic Bottle, System Dynamics, IoT, Bass Diffusion Model, Prototype

1. Introduction
Referring to the United Nations Department of Economic and Social Affairs data, the world's urban population is estimated to reach 72.8% in 2050. In 2018 it was only 55.3%, which impacted increasing waste production in cities up to 0.8 kg/capita/day (Kaza et al. 2018), as shown in Figure 1.

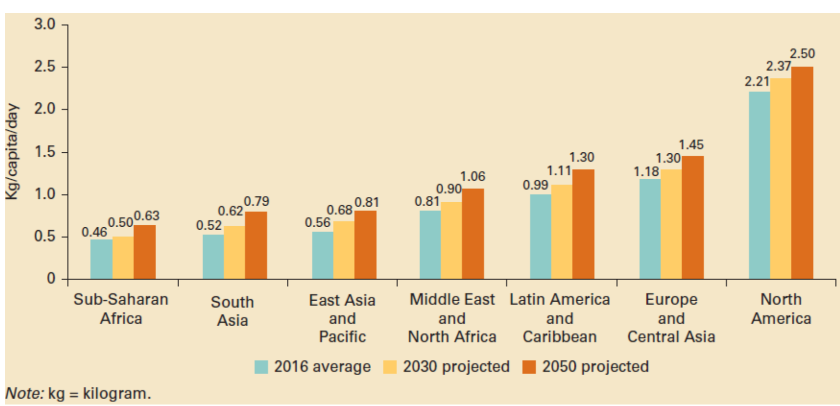

Figure 1. Projected waste production per capita (Kaza et al. 2018).

Indonesia is a country with 237 million, with 118 million living in urban areas as urbanites (BPS Census 2010). Urban waste management is critical to ensure the sustainability of the life of city residents. Poor waste management directly impacts the environment, such as air pollution, water pollution, and soil pollution, which in the long run will affect public health, which then has an impact on economic growth (Saha et al. 2017). Plastic is an easy thing to find in everyday life, especially in developing countries like Indonesia. Referring to world plastic production data released by the World Economic Forum, world plastic production reaches 322 million tons per year with various polymers, as shown in Figure 2.

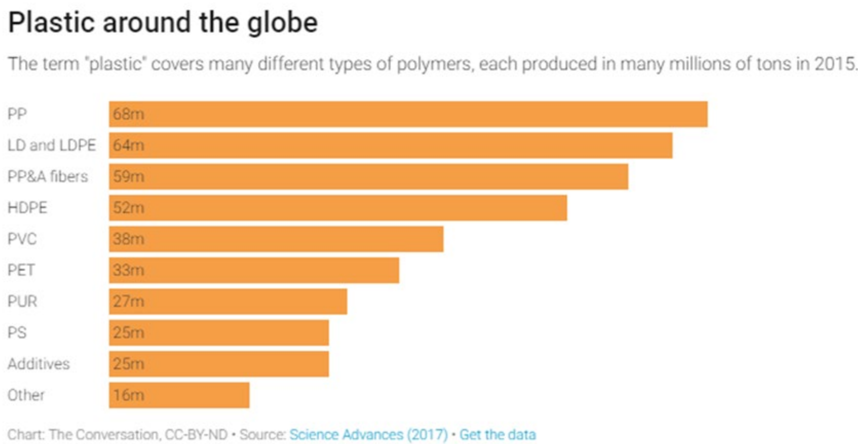

Figure 2. Plastic production in 2015 by type of polymer

The production and use of such a large amount of plastic must be balanced with a balanced waste management system, especially plastic, to avoid negative impacts. Plastic waste management is divided into three categories including disposal, incineration, and recycling. In 2015, 55% of plastic waste was thrown away, 25% was burned, and 20% was recycled. Based on historical data, it can be extrapolated using data from 1980 to 2050, as shown in Figure 3.

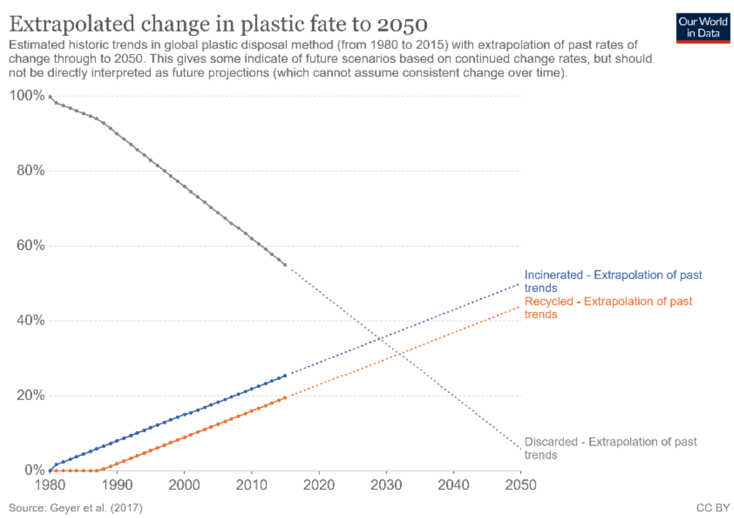

Figure 2. Estimation of plastic waste processing using trend extrapolation (Geyer et al. 2017)

Indonesia's waste production reaches 175,000 tons per day, with an average of 14% or as much as 24,500 tons is plastic waste. From DKI Jakarta's waste production of 7,164 tons per day, it can be estimated that around 920 tons of plastic waste are produced per day (National Waste Management Information System KLHK 2019). Unfortunately, 81% of the waste is not segregated, which causes difficulties in the recycling process. This is the cause of plastic waste to end up in the landfill and empties into the sea. Waste reduction and recycling efforts are urgently needed on a local scale better than expected on regional scale management. Waste segregation is urgently required even though its application is challenging with the current system and culture (Lu et al. 2018). The author develops an efficient, effective, and sustainable scheme. The study was conducted primarily focusing on the recycling of plastic bottle waste.

In addition, seeing that the trend of plastic waste management through recycling will increase until 2050, we need a technology that can campaign and change people's habits in managing and sorting plastic waste.

Recycling plastic waste has at least two advantages: (1) reducing the potential for pollution and environmental damage; (2) create job opportunities (Sahwan et al. 2005). We are currently in the era of industry 4.0, where technological advances in every aspect of life are trying to be combined. Industrial era 4.0 has evolved to develop the field of information and data technology. The cultural shift in the world of work has been influenced by the Internet of Things (IoT), with an exponential growth trend in intelligent devices connected to data, services, and people. The entire system has been linked by intelligent machines and data networks (Berawi 2018).

1.1 Objectives

The problem of waste, especially plastic waste, has become like a ticking time bomb and population growth. This growth was also driven by the high rate of urbanization, which led to an increase in daily waste production in big cities. Along with the trend and efforts to save the environment, recycling activities for plastic waste must be increased (Geyer et al. 2017). Innovation is needed to help solve this problem. During the industrial era 4.0, various application of technology concepts can be adapted to solve this problem. The essence of innovation management is the ability to generate valuable ideas for progress. Improving value design and technology is needed to meet the demands of equipment complexity and service improvement. Looking for additional functions that make the product different and enhancements to achieve the appropriate result is very important (Berawi 2015). Of the many IoT application concepts, a design process is needed to get products that have functions according to market expectations and their business feasibility.

This study was made to answer the following two questions:

1. How is the Bottle Reverse Vending Machine (DAUR) designed and prototyped?
2. What is the feasibility of investing in a Bottle Reverse Vending Machine (DAUR) based on NPV using dynamic system simulation?

2. Literature Review

2.1. Value Engineering

The application of Value engineering in the product design process has often been used.

1. Proof of the concept of Value Engineering can be applied in the mechanical product design process (Peng et al. 2016).
2. Proof of practical design and technology can result in satisfaction with the desire for a good product (Berawi 2015).
3. Proof that management, design, and technology can produce innovative designs (Suwartha 2015).

2.2. System Dynamics

System dynamic simulation is also applied in the product design process. The study has been done to obtain the relationship between the variables used. Some related studies are as follows:

1. The effect of system dynamics simulation has a positive impact on the overall system performance and final profit target (Briano et al. 2010)
2. Testing the interaction between innovation policy, innovation, firm competitiveness, and performance variables (Coad et al. 2019)
3. Testing the interaction between innovation policy, innovation, firm competitiveness, and performance variables (Golbazzadeh et al. 2016)
4. Re-model the finished product to see the truth of the model and its assumptions in the past through a system dynamics approach (Hui et al. 2011)
5. Modeling of project factors closely influences project performance (Ford et al. 1998).
6. Identify the dynamic relationship between product innovation and the innovation process using system dynamics (Kim 2009)
7. They are combining structural and dynamic complexity in process design engineering (Kasperek 2016).

2.3. IoT and Big Data Application at Smart Waste Management System

The application of IoT and Big Data analysis on the intelligent waste management system has been implemented, such as:

1. Survey to analyze the current state of IoT application in waste management (Pardini et al. 2018)

2. Provide support for decision making through georeferenced analysis through open data (Estrada et al. 2018)
3. They implement IoT wireless sensor networks for route optimization of waste management systems (Zeb et al. 2019).
4. Demonstrate how to increase competitive advantage with big data applications (Kubina 2015).
5. Proof of IoT applications can improve design optimization and technology performance (Berawi 2018).
6. Proof of Artificial Intelligence application can increase added value (Berawi 2020).
7. Proof of extensive data application can increase competitive advantage and business ethics (Berawi 2018).

2.4. Smart Waste Management System

Implementing intelligent waste management systems has also been carried out in several big cities in various countries. Some of the relevant studies are as follows:

1. Survey on the application of ICT for waste management (Anagnostopoulus et al. 2017).
2. They applied IoT (microcontroller and GPRS) to efficiently and economically monitor waste management systems (Sharmin 2016).
3. Recommend IoT applications to achieve an economical, efficient and sustainable waste management system (Lu et al. 2018).
4. They analyzed IoT applications in the Municipal Waste Management System (Saha et al. 2017).
5. They analyzed the plastic waste management system in Indonesia (Sahwan et al. 2005).
6. Make recommendations and suggestions for improvements to the Plastic Waste Management System (Hidayat et al. 2019).
7. Get a range of benefits from the plastic bottle waste supply chain (Kristina 2017).
8. Make recommendations on IoT use for monitoring automated waste collection systems (Popa et al. 2017).
9. They applied IoT application for the intelligent waste management system (Srikanth 2019).
10. They implement IoT as an early notification system to the authorities on full bins (Chaudhari 2019).

3. Methods

A multidisciplinary approach is carried out with steps to find answers to research questions, as shown in figure 4.

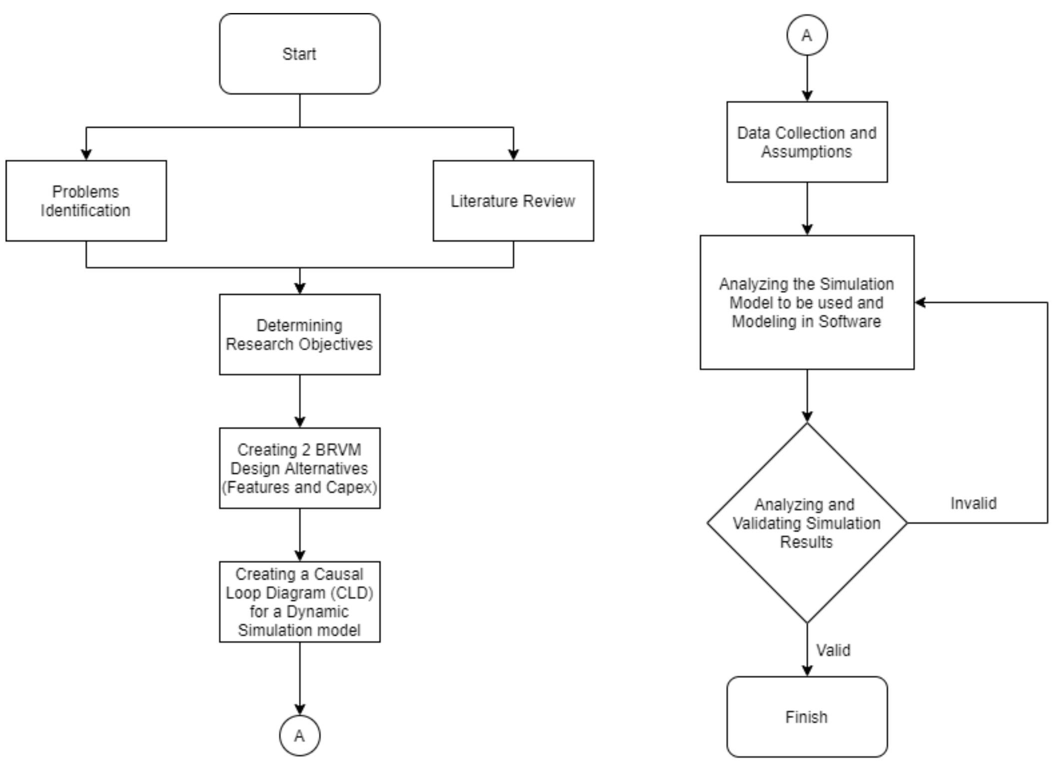

Figure 3. Flow chart of research

4. Data Collection and Analysis

4.1 Bottle Reverse Vending Machine (DAUR) Product Design

The general plastic recycling business process is depicted in the figure. The DAUR business process starts from collecting, separating, counting, washing, drying and selling to factories (Sahwan et al. 2017). This Bottle Reverse Vending Machine (DAUR) is an integral part of the plastic bottle recycling business process. Before carrying out the design, the author collects data related to the tool's needs and purposes. The conditions and goals of using these tools are summarized as the following specifications in Table 1.

Table 1. Design requirements and objectives

Features	Mandatory	Variable	Sub Variable
Has a minimum storage capacity of 55 Liters	Yes	X1.1	Bins
Has an opening and closing mechanism	Yes	X1.1; X3.2; X3.5; X5.1; X5.2	Bins; RFID; Actuators; Architecture; Social Context
Has a bottle return mechanism that does not meet the criteria	Yes	X2.1; X3.3; X3.6; X4.1; X5.2; X5.3	Processing; Sensors; Camera; DSS; Social Context; Experimental Data
Has a user identification mechanism	Yes	X3.2	RFID
Has a storage capacity sensor	Yes	X3.3; X4.1; X5.1	Sensor; DSS; Architecture
Have the ability to know the contents of the bottle	No	X2.1; X3.3; X3.6; X4.1; X5.2; X5.3	Processing; Sensors; Camera; DSS; Social Context; Experimental Data
Have the ability to know the type of bottle	No	X2.1; X3.3; X3.6; X4.1; X5.2; X5.3	Processing; Sensors; Camera; DSS; Social Context; Experimental Data
Have the ability to determine the price of the bottle	Yes	X2.1; X3.3; X3.6; X4.1; X5.2; X5.3	Processing; Sensors; Camera; DSS; Social Context; Experimental Data
Have a vandalism prevention mechanism	Yes	X1.1; X2.1; X3.3; X3.5; X3.6; X4.1; X5.2; X5.3	Bins; Processing; Sensors; Actuators; Camera; DSS; Social Context; Experimental Data
Have a mechanism to communicate with the server	Yes	X2.1; X2.2; X3.4; X4.3; X5.1	Processing; Bins Location; WSN; Scheduling; Architecture
Have the ability to recognize the location	No	X2.1; X2.2; X3.4; X4.2; X4.3; X5.1	Processing; Bins Location; WSN; GIS; Scheduling; Architecture

The author has concluded the design concepts that may be made to meet the design requirements and objectives from the table above. Meanwhile, the overall cost (Life Cycle Cost) of this business has been calculated separately. The components that are taken into account include:

1. Investment cost/Capex: DAUR machines, transportation equipment, chopping machines, etc.
2. Operational Costs/Opex: Labor, transportation equipment, water, electricity, land rent, transportation, advertising, etc.
3. Cost of Money: Depreciation, interest rates, inflation, taxes, etc

4.2 Alternative Design and Cost Calculation of Bottle Reverse Vending Machine (DAUR) Products

To meet the design requirements and objectives requested by the user, the author seeks to create alternative designs that can be an option. In addition to the difference in features, this alternative also has a difference in the investment cost. So that in this study, it can be seen the effect of changes in equipment investment costs on the adoption rate and NPV. From Table 2 shown below, we can see a significant difference between alternative design one and alternative design 2. In the relative rank column, there are at least 4 different design parameter points in the two alternatives.

Table 2. Specification and design alternatives

Design Parameters	Design Alternatives		Features	Variable	Sub Variable	Relative Rank According to Min. Requirements	Normalized Weight
	Design 1	Design 2					
Inductive Sensor	Yes	Yes	Knowing the condition of the contents of the bottle	X3.3	Sensors	5	0,064
Capacitive Sensor	No	Yes	Knowing the condition of the contents of the bottle	X3.3	Sensors	3	0,038
Bottle Rotator Motor	Yes	Yes	Rotate the bottle	X3.5	Actuators	8	0,103
Object Presence Sensor	Yes	Yes	Finding the Object	X3.3	Sensors	9	0,115
Contour Sensor	No	Yes	As a bottle shape AI input	X3.3	Sensors	2	0,026
Barcode Scanner	Yes	Yes	Knowing the type of bottle according to product registration	X3.3	Sensors	10	0,128
Camera	Yes	Yes	Prevent fraud, AI bottle reader	X3.6	Camera	6	0,077
Level Sensor	Yes	Yes	Storage level monitoring	X3.3	Sensors	11	0,141
GPS	No	Yes	Bins position and scheduling	X4.2	Geographic Information System	4	0,051
RFID/QR Code	Yes	Yes	Recognize the user to log in	X3.2	RFIDs	12	0,154
Actuators	Yes	Yes	Distributing bottles (Accept/Reject)	X3.5	Actuators	7	0,090
Weight Sensor	No	Yes	Price calculation by weight	X3.3	Sensors	1	0,013
Overall Function Score	**0,872**	**1**				78	1

The differences between the two design alternatives are:

1. Weight sensor: Serves as a sensor to estimate the weight of the bottle and convert it into a price. In addition, it can serve as a verification of the contents of the bottle. However, the addition of the weight sensor function as mentioned above can be fulfilled by several other sensor combinations.
2. Contour sensor: serves as a sensor to detect and verify objects entered by the user. To ensure that the item is inserted in a bottle and is not an attempt of vandalism and fraud. However, the addition of the contour sensor function as mentioned above can be fulfilled by several other sensor combinations.
3. 3. Capacitive sensor: Serves as a sensor to detect the bottle and verify the state of the contents of the bottle. However, the addition of the weight sensor function as mentioned above can be fulfilled by several other sensor combinations.
4. 4. GPS: Functions to schedule bottle pick-ups automatically through information managed by the server (Popa et al. 2017). Given the inefficient field conditions for automatic scheduling, this feature is not needed.

Simplification of features is carried out to reduce investment costs for DAUR machines. However, there are still alternative designs with exclusive features if its function is needed to improve service quality or prevent fraud.

4.3. Bottle Reverse Vending Machine (DAUR) Product Prototype

As in the discussion of point 4.2 above, the difference between alternative design one and alternative design 2 is only in some features and sensor requirements. While the physical appearance of the two is made identical to facilitate modifications according to changing user needs, such as the shape of the casing, mounting, PCB. In addition, the programming architecture is also made as identical as possible by completing all existing features.

The difference, of course, has an impact on the price difference between the two alternatives. However, with an identical design, it is possible to easily make feature adjustments and sensor additions without making significant changes. The prototype design for the DAUR machine is as shown in Figure 5.

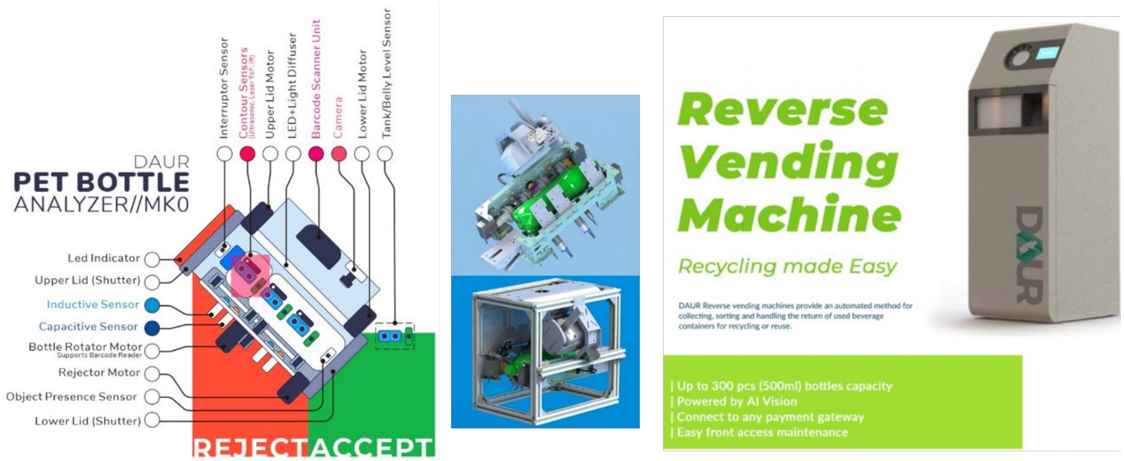

Figure 4. Prototype design of DAUR machine

4.4. Causal Loop Diagram

Causal Loop Diagram is an effective method to describe the relationship between variables in the system in system dynamics. Causal Loop Diagram allows us to understand the nature of the variables used in the simulation in more detail. Then the model will be refined by adding quantitative parameters commonly referred to as stock and flow diagrams. At this stage, parameters and variables will be determined and calculated from the data that has been collected. Any changes in research and development costs, production costs will have an influence on design, product performance, and product quality (Coad et al. 2019). In this study, modeling and simulation of two cases with different alternative designs were carried out to show the effect of cost on adoption rate and changes in NPV.

4.4.1. Simulation Model and Sub-System

System dynamic modeling begins with the creation of a Causal Loop Diagram. In this study, the causal loop diagram of the entire system can be seen in Figure 6. This system is made following the purpose of the study, namely to see the effect of design or equipment investment costs on the overall project adoption rate and NPV. The data used as input parameters and variables are obtained from publicly accessible data. In figure 6, there are several loops which are balancing loops and reinforcing loops.

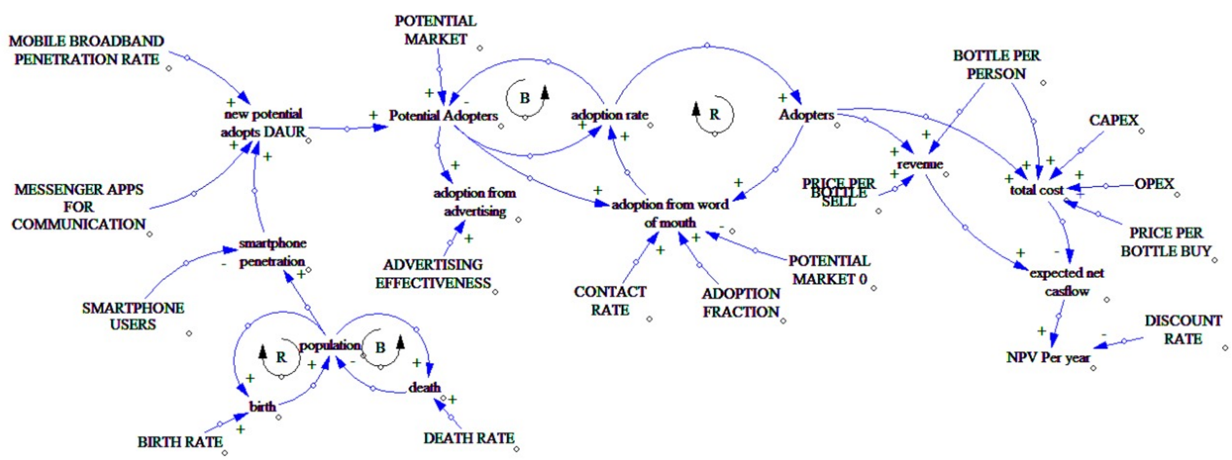

Figure 5. Causal loop diagram

Table 3. Description of the loops

Loops	Descriptions
R1: Birth Rate-Population	This loop indicates the relationship between birth rate and population size. It is reinforcing because the birth rate will increase the population.
B1: Death Rate-Population	This loop indicates the relationship between mortality and population. It is balancing because the death rate will reduce the population.
R2: Adoption Rate-Adopters-Word of Mouth	This loop indicates the relationship between adoption rate, number of adopters, and adoption from word of mouth. This loop shows the dynamics of the adoption process from users to other people who have not used it and is reinforcing.
B2: Adoption Rate-Potential Adopters	This loop indicates the relationship between the adoption rate and the number of potential adopters and is balancing.

The Causal Loop Diagram below can be understood by reading sequentially starting from a factor whose value is not directly influenced by other factors. For example, the mobile broadband penetration rate factor has a positive influence on the number of new potential adopters which will then have a positive impact on increasing the number of potential adopters and so on. In addition, factors such as price per bottle (sell), bottle per person, capex, opex, price per bottle (buy), and discount rate will be simulated for sensitivity analysis.

4.4.2. Technology Adoption based on Smartphone

The changing times towards the era of modern technology require people to adopt technology in several fields. Before transforming technology into society, proper analysis of the conditions of the community needs to be carried out to see the community's acceptance of the technology to be applied (Abbasi et al. 2016). Currently, banking companies and other companies have used smartphone-based technology to attract attention and facilitate their business processes. This is done to cut costs so that business processes become more efficient and customer service is maximized (Aminah. 2019).

4.4.3. Assumptions and Calculations

There are several methods for data collection such as (Table 4):

1. Data used by previous qualitative and quantitative research
2. Secondary data found on the internet but published by an agency or institution that has a role in related research.

Table 4. Data assumptions and calculations

Number	Variable	Value1	Value2	Unit	Source
1	Birth Rate	0,014	[redacted]	ppl	Delloite Konsultan Indonesia, 2019.
2	Death Rate	0,0088	[redacted]	ppl	Bappenas, 2013
3	Smartphone Users	87.800.000	[redacted]	ppl	Statista, 2020
4	Mobile Broadband Penetration rate	0,6834	[redacted]	fraction	Statista, 2020; Aminah, 2019
5	Mesengger Apps for Communication	3	[redacted]	apps	Aminah, 2019
6	Potential Market	137.000	[redacted]	ppl	Calculation based on BPS data
7	Advertising Effectiveness	0,27	[redacted]	fraction	Gorman, 2021
8	Contact Rate	2	[redacted]	ppl/wk	Aminah, 2019
9	Adoption Fraction	0,25	0,2	fraction	Statistia, 2020
10	Price per Bottle (Sell)	480	[redacted]	IDR/unit	Calculation based on BPS data
11	Price per Bottle (Buy)	200	[redacted]	IDR/unit	Calculation based on BPS data
12	Bottle per person	1,67	[redacted]	Bottle	Calculation based on BPS data
13	Capex	90,78	104,96	IDR/unit	Calculation based on writer data
14	Opex	168,46	[redacted]	IDR/unit	Calculation based on writer data
15	Discount Rate	7,6	[redacted]	%	Central Bank of Indonesia, 2020

In this study, two simulations were carried out with variations in investment costs/CAPEX. However, there is an adjustment for the adoption fraction considering that every change in research and development costs, production costs will have an influence on design, product performance, and product quality (Coad et al. 2019). In a report entitled 21st Century Health Care Challenges: A Connected Health Approach issued by Delloite Indonesia, an estimate of the population growth of Indonesia's population in 2025, 2035, and 2045 is made using BPS data in 2019. These figures are processed by the authors into numbers to determine birth rate factor. As for the death rate, the 2013 Bappenas report stated the death rate for the Indonesian population over the last ten years.

This study is closely related to the use of smartphones, so that the determination of the number of smartphone users is obtained from a survey report conducted by Statista in 2020. The magnitude of the network penetration factor is also an important factor that influences each other with the number of smartphone users. The Statista report in 2020 and the study report conducted by Aminah in 2019 showed that the penetration of mobile broadband networks in Indonesia had reached 0.6843. In line with the two things above, the use of smartphone networks, access to mobile broadband, and the use of messenger applications as a means of communication also produce a contact rate factor of two people per week. This contact rate factor is an important factor in determining the adoption rate as described in the Bass Diffusion Model theory (Bass. 1969; Sterman. 2000; Mutingi and Matope. 2013).

The factors described above are constant in this study. As explained earlier, this study focuses on designing and prototyping to see the impact of changes in the investment cost of the tool on the economic value. Therefore, other factors such as market potential, price per bottle, bottle per person, capex, opex, and discount rate are factors that need to be analyzed for sensitivity to see their impact on the economy. Except for the discount rate factor originating from the deposit interest rate issued by Bank Indonesia in 2020, other factors are derived from calculations that are closely related to the total population.

4.4.4. Formula parameters dan sub-systems

The basic formula for each input in the model can be seen in Table 5, shown below.

Table 5. Parameter formulas

Variabel	Formula
Smartphone penetration	SMARTPHONE USERS'/Population
New Potential Adopt daur	MESSENGER APPS FOR COMMUNICATION'*'MOBILE BROADBAND PENETRATION RATE'/'smartphone penetration'
Potential Adopter	'POTENTIAL MARKET'-Adopters
Adoption Rate	'adoption from advertising'+'adoption from word of mouth'
Adoption from advertising	('ADVERTISING EFFECTIVENESS'*Potential_Adopters)
Adoption from word of mouth	(Potential_Adopters * Adopters *'CONTACT RATE'*'ADOPTION FRACTION'/'POTENTIAL MARKET')
Revenue	(Adopters*'PRICE PER BOTTLE SELL'*'BOTTLE PER PERSON')
Total cost	(('CAPEX PER BOTTLE'+'OPEX PER BOTTLE'+'PRICE PER BOTTLE BUY')*Adopters*'BOTTLE PER PERSON')
expected cash flow	(revenue-'total cost')
Cumulative Discounted cash flow per year	NPV('expected cashflow','DISCOUNT RATE')
Birth	(BIRTH_RATE*Population)
Death	(DEATH_RATE*Population)

4.5. Model Validation and Test

When the stock and flow model has been developed, the model must be validated using actual data. There are several recommended methods to test the accuracy of dynamic system models (Sterman. 2002). In this study, a comparison of the model with available statistical data was used. Such as the model of the number of parameters of the birth rate and death rate, which is validated with BPS data. In this study, 2020 was chosen as the era of the start of IoT, which began to penetrate people's lives and was simulated until 2030. This is due to the research limitations determined by the authors, who cannot estimate the factors of government policy, people's habits, technological developments, and environmental conditions. In addition, as explained in the section before that the forming factors and the basic formula of the dynamic system model built are influenced by population factors. Thus, the population factor and its derivatives are the main factors that have a major impact on the dynamic system model that is made so that it requires a validation test of the population factor so that the dynamic system made becomes valid and can be accounted for.

This test aims to test the system response to reference data. Figure 7 and Table 6 show the system response from the primary variables, namely variables related to the population. From the figure, it can be seen that the patterns and responses formed look very similar to the reference data. Although the difference between the model and the reference data can be considered as an error, it can be quantified by calculating the coefficient of determination (R-Squared).

Table 6. Projection (Bappenas, 2019) vs. simulated behavior of population

Year	Fertility (14/1000 ppl/year	Mortality (8,8/1000 ppl/year)	Calculated Population	Total Population	% Error
2020	149.030	93.676	10.700.354	10.645.000	0,52%
2021	150.207	94.416	10.756.145	10.729.100	0,25%
2022	151.341	95.129	10.812.358	10.810.100	0,02%
2023	152.429	95.813	10.868.974	10.887.800	-0,17%
2024	153.474	96.469	10.925.979	10.962.400	-0,33%
2025	154.476	97.099	10.983.356	11.034.000	-0,46%
2026	155.414	97.689	11.041.081	11.101.000	-0,54%
2027	156.267	98.225	11.099.123	11.161.900	-0,57%
2028	157.037	98.709	11.157.451	11.216.900	-0,53%
2029	157.725	99.142	11.216.034	11.266.100	-0,45%

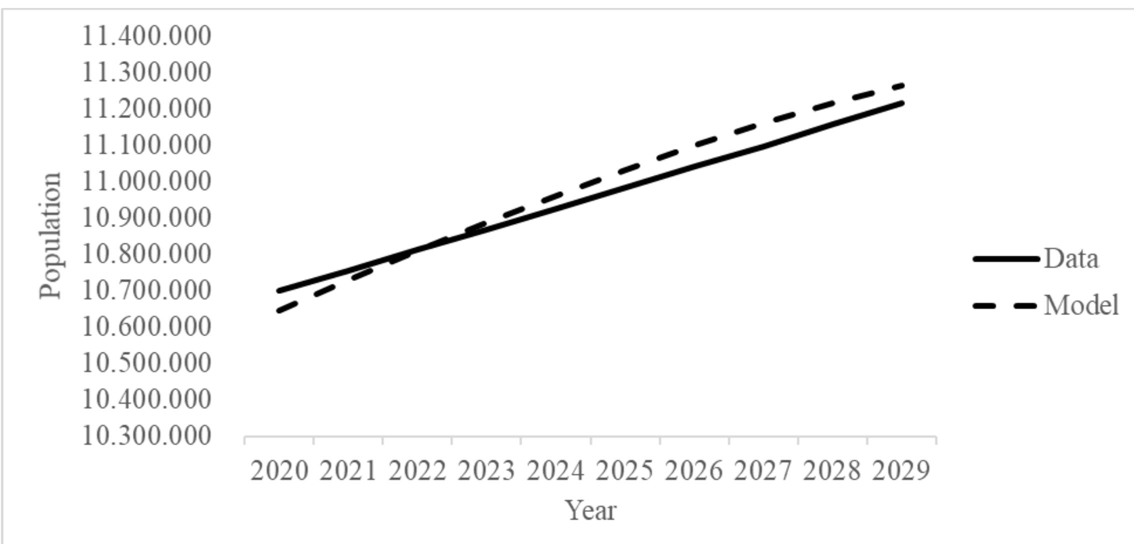

Figure 6. Projection (Bappenas, 2019) vs. simulated behavior of population

With a calculation error of less than ±0.6%, the coefficient of determination (R-Squared) can then be calculated. The calculation results show that the R-Squared value is 0.993. The calculation results are obtained through calculations using the formula below.

$$R^2 = \frac{1}{n}\sum \frac{(X_d - \bar{X}_d)(X_m - \bar{X}_m)}{s_d s_m}$$

Where X_m and X_d represent the simulation output and reference data.

5. Results and Discussion

In this chapter, we will discuss the analysis of the simulation results and their comparison with the relevant literature. The results of this study include the prototype design of the DAUR engine which is produced with an explanation of its features. In addition, this chapter also describes the results of the dynamic system simulation carried out to see the effect of equipment investment costs/capex on the adoption rate and also the overall net present value of the project. Sensitivity analysis was also carried out on other variables to see the effect of each variable on the net present value.

5.1 DAUR Machine Prototype

The author has simulated and optimized the design of the optimal DAUR machine to meet the needs and objectives desired by the user. The differences in the four features between alternative design one and alternative design two have been resolved into an identical design. This aims to facilitate the adjustment of machine features in meeting the design and requirements of the user according to the features in Table 2. In addition, the identical design also affects the ease of maintenance, interchangeability of spare parts, and the efficiency of design and manufacture time. The prototype design of the DAUR machine that can represent the two alternative designs can be seen in Figure 8. At the same time, the display of the DAUR machine design application can be seen in Figure 9.

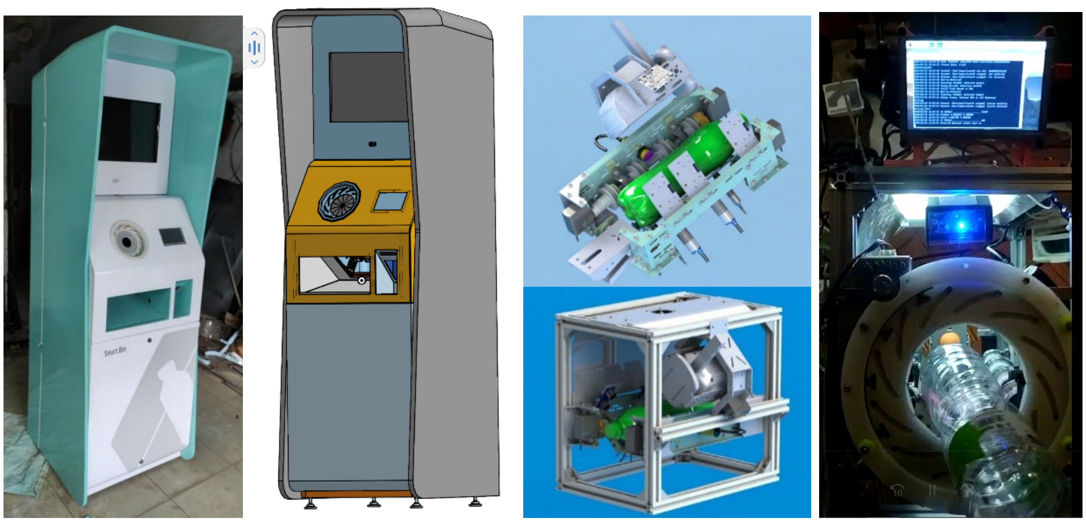

Figure 7. Design and prototype DAUR machine

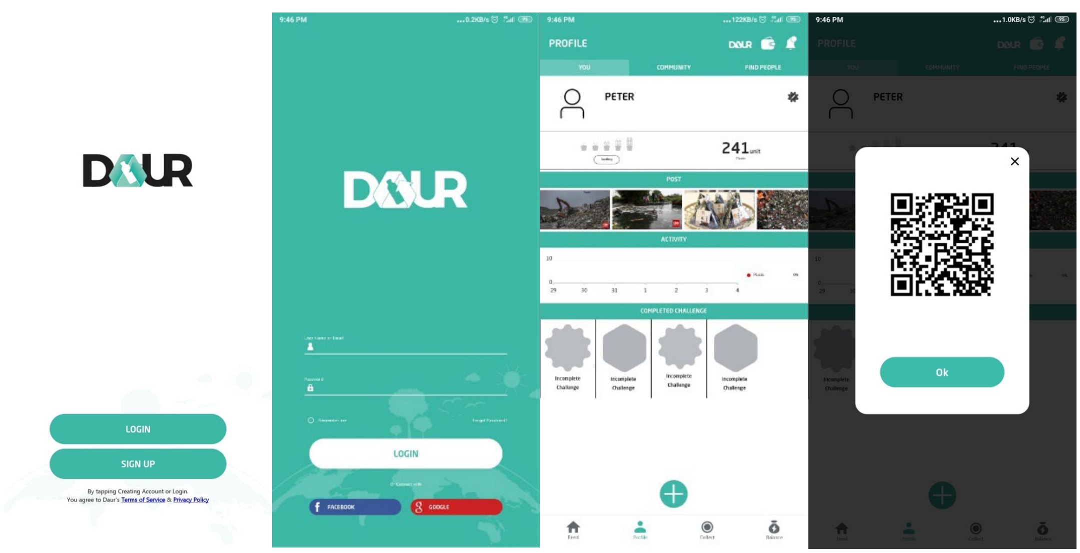

Figure 8. Design and prototype of DAUR mobile apps.

Furthermore, testing has been carried out on the designs and prototypes made. This test is carried out to determine the response of the machine, the reliability of Machine Learning and Artificial Intelligence features, detect the level of storage space, and integration with payment systems and applications. In the order of verification of bottles that are inserted into the machine, the machine will try to read the barcode first to facilitate and speed up the verification process. After that, the bottle is verified that it is empty and that it is actually made of plastic. The verification process using Artificical Intelligence is carried out when the barcode on the bottle is unreadable and/or not registered in the system database. A number of embedded sensors will evaluate according to the specified parameters. The results of testing the AI features on this prototype achieve a reliability of 90% and an average verification time of 9 seconds.\

5.2 Results of System Dynamic Simulations

5.2.1. Simulation results of Design Alternative 1

By inputting the parameters and variables as shown in Table 4 column value 1, the simulation results are obtained as shown in Figure 10 and Table 7.

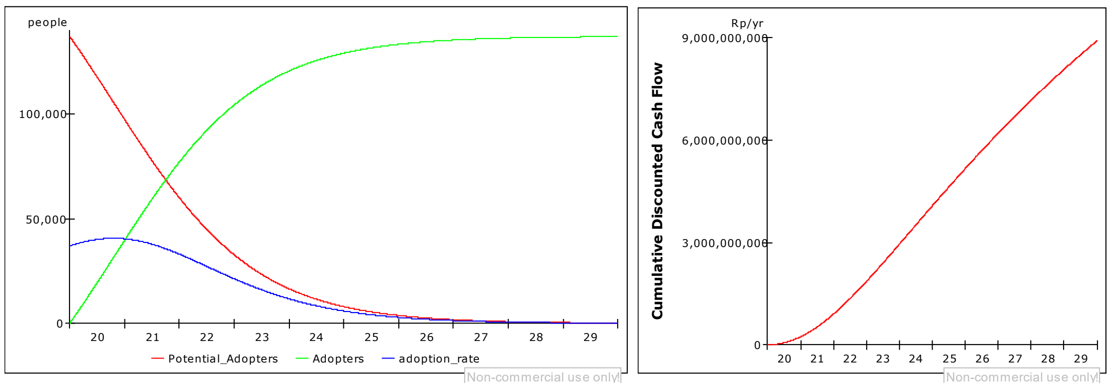

Figure 9. Simulation results of design alternative 1

Table 7. Table of simulation results of design alternative 1

Time	Potential Adopters	Adopters (people)	adoption_rate (people/yr)
Jan 1, 2020	137,000.00 people	0.00	36,990.00
Jan 1, 2021	97,403.00 people	39,603.23	40,377.18
Jan 1, 2022	59,958.90 people	77,053.59	33,050.39
Jan 1, 2023	32,751.55 people	104,267.23	21,306.10
Jan 1, 2024	16,537.18 people	120,487.93	11,737.04
Jan 1, 2025	7,991.55 people	129,039.91	5,921.33
Jan 1, 2026	3,778.20 people	133,259.65	2,857.64
Jan 1, 2027	1,769.20 people	135,275.08	1,351.15
Jan 1, 2028	826.59 people	136,224.15	634.13
Jan 1, 2029	387.68 people	136,669.55	298.05
Jan 1, 2030	184.05 people	136,879.70	141.64

(Rp/yr)

Time	Cumulative Discounted Cash Flow	expected cashflow
Jan 1, 2020	0.00	0.00
Jan 1, 2021	234,691,926.99	1,373,012.29
Jan 1, 2022	896,448,395.50	2,671,386.21
Jan 1, 2023	1,851,627,225.15	3,614,861.53
Jan 1, 2024	2,945,697,346.02	4,177,220.14
Jan 1, 2025	4,068,267,293.13	4,473,710.59
Jan 1, 2026	5,160,027,054.71	4,620,005.52
Jan 1, 2027	6,194,994,599.98	4,689,878.71
Jan 1, 2028	7,164,378,169.32	4,722,782.26
Jan 1, 2029	8,067,246,384.47	4,738,223.92
Jan 1, 2030	8,905,971,745.00	4,745,509.84

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In Figure 10, it can be seen that the number of adopters is starting to stagnate, which is marked by a decrease in the adoption factor. The second year is the year with the highest peak adoption rate, which means adding the largest adopters in the simulation period. This shows that this kind of technology is quite in demand by the public. While the NPV at the end of the tenth year showed 8.9 billion rupiahs, this project is feasible (Sullivan. 2012).

The simulation period in this study is more than sufficient if you look at the simulation results in figure 10 and table 7, which show conditions that have started to saturate in the fourth year. In the second year, the number of adopters grew exponentially. Despite the size of the market, this can lead to a more rapid saturation. The growth is also triggered by the high number of smartphone users among potential adopters. At the same time, the slow growth of adopters is usually influenced by the lack of word-of-mouth influence (Morecroft. 2015). The stagnation that occurs due to a saturated market can be seen as an indicator that almost all potential adopters have become adopters (Hassan and Minato. 2018). Thus, the dynamic behavior of smartphone-based technology adoption, as discussed above, strengthens the current model following previous findings from studies of new products and technology adoption processes stated in the Bass Diffusion Model (Bass. 1969; Sterman. 2000; Mutingi and Matope. 2013).

5.2.2. Simulation results of Design Alternative 2

By inputting the parameters and variables as shown in Table 4 column value 1, the simulation results are obtained as shown in Figure 11 and Table 8.

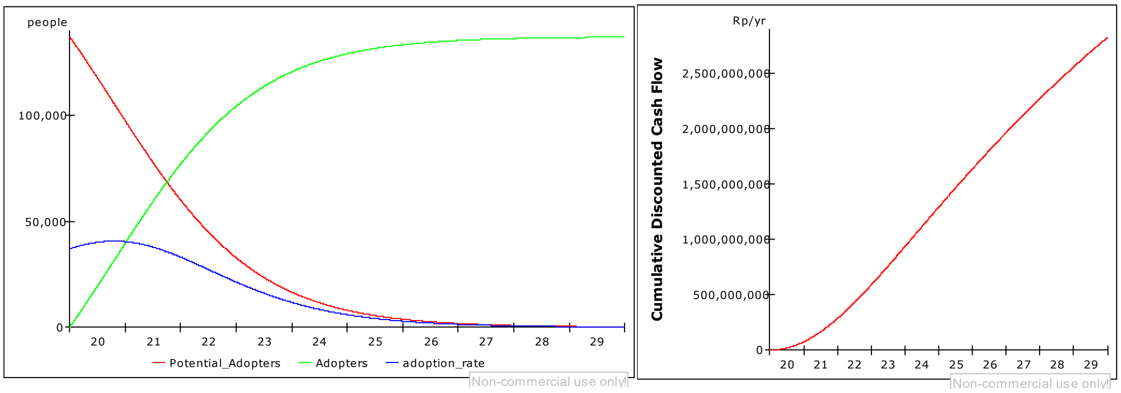

Figure 10. Simulation Results of Design Alternative 2

Table 8. Table of Simulation Results of Design Alternative 2

Time	Potential Adopters	Adopters (people)	adoption_rate (people/yr)
Jan 1, 2020	137,000.00 people	0.00	36,990.00
Jan 1, 2021	97,403.00 people	39,603.23	40,377.18
Jan 1, 2022	59,958.90 people	77,053.59	33,050.39
Jan 1, 2023	32,751.55 people	104,267.23	21,306.10
Jan 1, 2024	16,537.18 people	120,487.93	11,737.04
Jan 1, 2025	7,991.55 people	129,039.91	5,921.33
Jan 1, 2026	3,778.20 people	133,259.65	2,857.64
Jan 1, 2027	1,769.20 people	135,275.08	1,351.15
Jan 1, 2028	826.59 people	136,224.15	634.13
Jan 1, 2029	387.68 people	136,669.55	298.05
Jan 1, 2030	184.05 people	136,879.70	141.64

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(Rp/yr)

Time	Cumulative Discounted Cash Flow	expected cashflow
Jan 1, 2020	0.00	0.00
Jan 1, 2021	74,386,940.25	435,184.05
Jan 1, 2022	284,134,414.37	846,711.04
Jan 1, 2023	586,883,773.67	1,145,750.91
Jan 1, 2024	933,655,517.19	1,323,993.67
Jan 1, 2025	1,289,460,442.62	1,417,968.00
Jan 1, 2026	1,635,499,904.62	1,464,337.01
Jan 1, 2027	1,963,538,750.86	1,486,483.72
Jan 1, 2028	2,270,790,383.15	1,496,912.68
Jan 1, 2029	2,556,959,595.85	1,501,807.00
Jan 1, 2030	2,822,798,366.19	1,504,116.32

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In Figure 11, it can be seen that the number of adopters is starting to stagnate, which is marked by a decrease in the adoption factor. The second-year is the year with the highest peak adoption rate, which means the addition of the largest adopters in the simulation period. This shows that this kind of technology is quite in demand by the public. While the NPV at the end of the tenth year showed a figure of 2.8 billion rupiahs, which means this project is feasible (Sullivan. 2012).

The simulation time in this study is more than sufficient if you look at the simulation results in Figure 11 and Table 8, which show conditions that have started to saturate in the fourth year. In the second year, the number of adopters grew exponentially. Despite the size of the market, this can lead to a more rapid saturation. This is also triggered by the high number of smartphone users among potential adopters. At the same time, the slow growth of adopters is usually influenced by the lack of word-of-mouth influence (Morecroft. 2015). The stagnation that occurs due to a saturated market can indicate that almost all potential adopters have become adopters (Hassan and Minato.2018). Thus, the dynamic behavior of smartphone-based technology adoption, as discussed above, strengthens the current model by previous findings from studies of new products and technology adoption processes stated in the Bass Diffusion Model (Bass. 1969; Sterman. 2000; Mutingi and Matope. 2013).

The simulation results of this second alternative design show a very significant decrease in the NPV value when compared to the NPV value in alternative design 1. The reduction in the NPV value in the last year by 68% compared to alternative 1 is an essential concern for the authors considering that the increase in equipment investment costs is only 16 % compared to alternative design 1.

5.2.3. Sensitivity Analysis Simulation Results

Although it is known the effect of the increase in investment costs on the economic feasibility as represented by the NPV value, it is necessary to test the sensitivity of other supporting factors (Table 9). This sensitivity test is intended to determine the effect of changes in a factor on the simulation results of dynamic systems, especially economic feasibility.

Table 9. Sensitivity Test with Parameter Value Variation +20% and -20%

No.	Variable	Baseline/Alternative 1	Case1	Case2	Case3	Case4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12	Unit
1	Birth Rate	0,014													ppl
2	Death Rate	0,0088													ppl
3	Smartphone Users	87.800.000													ppl
4	Mobile Broadband Penetration rate	0,6834													fraction
5	Mesengger Apps for Communication	3													apps
6	Potential Market	137.000													ppl
7	Advertising Effectiveness	0,27													fraction
8	Contact Rate	2													ppl/wk
9	Adoption Fraction	0,25													fraction
10	Price per Bottle (Sell)	480	576	384											IDR/unit
11	Price per Bottle (Buy)	200			240	160									IDR/unit
12	Bottle per person	1,67					2,00	1,34							Bottle
13	Capex	90,78							108,94	72,62					IDR/unit
14	Opex	168,46									202,15	134,77			IDR/unit
15	Discount Rate	7,6											9,12	6,08	%

The discussion in sections 5.2.1 and 5.2.2 has shown that the effect of changes in the value of investment costs has a significant impact on the NPV value. Furthermore, the authors conducted a sensitivity test to see the effect of each factor on the NPV value. The tested factors are factors that have a direct impact on the NPV value based on the dynamic system simulation model created. In addition, the factors in this sensitivity test are also factors whose values can be easily changed from the company's internal and/or easy to fluctuate due to market changes. These factors are price per bottle (sell), price per bottle (buy), bottle per person, capex, opex, and discount rate. Variation values of +20% and -20% are given to see the effect of each factor on the selected baseline, namely alternative design 1.

The simulation results for the 12 sensitivity test cases that are intended are very diverse. In accordance with the author's hypothesis that the number of factors related to the population does not change much because it uses the same value as in alternative design 1. Next, the author will focus on the effect of the analysis of the sensitivity test results with variations of each variable by +20% and - 20%. The summary of this information can be seen in the Table 10 and Figure 12 below.

Table 10. Simulation Results of Sensitivity Analysis

Variable	NPV		
	20%	0	-20%
Price per Bottle (Sell)	50.089.656.115	8.905.971.745	- 32.277.712.625
Price per Bottle (Buy)	- 8.253.896.742	8.905.971.745	26.065.840.232
Bottle per Person	10.665.834.425	8.905.971.745	7.146.109.065
Capex	1.115.391.452	8.905.971.745	16.695.552.038
Opex	- 5.546.927.489	8.905.971.745	23.358.870.979
Discount Rate	8.210.212.585	8.905.971.745	9.674.959.622

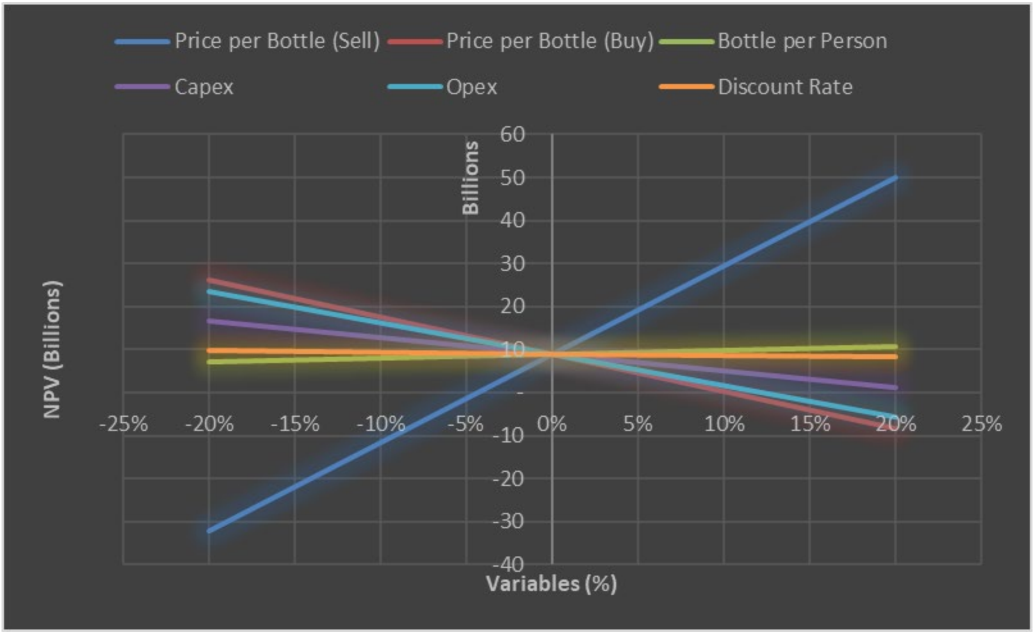

Figure 11. Graphic of Sensitivity Analysis Simulation Results

The analysis of the simulation results of the sensitivity test cases can be done more easily by looking at table 10. The NPV value from the simulation results of alternative design 1 is used as a reference value/baseline of 8.9 billion rupiah. The color assignment in table 10 means the comparison of the NPV value of each case to the reference NPV value. The green color represents an NPV value that is greater than the reference NPV value, which means that it is more economically feasible. The yellow color represents an NPV value that is smaller than the reference NPV value, which means it is not more profitable but still feasible because it has a negative NPV value. While the red color represents the NPV value which is smaller than the reference NPV value and is negative, which means it is not economically feasible.

The simulation results are also depicted in Figure 12 which is depicted in graphical form. The difference between the extreme values can be interpreted as the slope of the line which can be interpreted as the significance/sensitivity of the influence of each factor on the simulation results. The magnitude of the effect of changes in factor values starting from those with the greatest significance/sensitivity sequentially, namely price per bottle (sell), price per bottle (buy), opex, capex, bottle per person, and discount rate. Although influenced by economic policies and consumption of packaged drinks by the public, the significant changes in the bottle per person factor and the discount rate are factors that have very low influence on NPV. This sensitivity test was carried out only to see the effect of each factor on the NPV value. Meanwhile, for changes in the combination of several factors, it is necessary to do a simulation using a dynamic system simulation model that has been developed in this study.

5.3 Proposed Improvements

This DAUR machine is worth investing in with an NPV value greater than 0. In addition, this engine can also meet the design requirements and objectives specified by the user. The suggestions given by this research for future research are as follows.

1. System dynamic simulation modeling can be improved in further research by involving policy factors and government commitment to plastic waste management.
2. Simulation modeling of this dynamic system can be improved in further research by involving community cultural factors in the use of plastic bottles, especially for urban communities.
3. Please conduct sensitivity analysis to changes in the buying and selling prices of plastic bottles.

6. Conclusion

Based on the data that has been collected, processed and analyzed by the author, it can be concluded that the results of this study are as follows.

6.1. Answers to Research Questions 1.

How was the Bottle Reverse Vending Machine (DAUR) designed and prototyped?

The design and prototype of the Bottle Reverse Vending Machine (DAUR) has been successfully created as shown in Figures 8 and Figure 9. In addition, a series of systems have been tested which include the DAUR machine, user applications, and support pages. Testing of the DAUR engine has also been carried out in accordance with the design specifications set out in table 2 and is proven by the results of the engine tests that have been carried out.

6.2. Answers to Research Questions 2.

What is the feasibility of investing in a Bottle Reverse Vending Machine (DAUR) based on NPV using dynamic system simulation?

The investment in a Bottle Reverse Vending Machine (DAUR) based on NPV is well worth it. Both in alternative design 1 and alternative design 2 (Sullivan, 2012). The results of the dynamic system simulation show that an increase in capex by 16% can have an impact on decreasing the NPV value by 68%. The analysis of the sensitivity test results also shows that the factors whose changes have the greatest influence on the reference NPV value are price per bottle (sell), price per bottle (buy), opex, capex, bottle per person, and discount rate. Meanwhile, for changes in the combination of several factors, it is necessary to do a simulation using a dynamic system simulation model that has been developed in this study.

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Biography

Joko Wisnugroho is a project engineer with six years of professional experience in the oil and gas sectors. Currently, he works as an engineer at the national oil company of Indonesia. Several projects have been completed, such as fuel terminal, LPG terminal, pipeline, and other downstream projects. He holds a bachelor's degree in Mechanical Engineering from Bandung Institute of Technology (ITB) and completing his master's degree in project management at the University of Indonesia. He also has several professional certifications, such as a professional engineer from the Indonesian Engineers Association (PII) and also a Certified Cost Professional from the American Association of Cost Engineers (AACE - International). With his colleagues, he also started Hardtmann Mekatroniske a company that has a business in technology applications. As technology grows and the industry develops, numerous challenges and questions arise. Hardtmann Mekatroniske is more than ready to assist your business development to be part of the movement. Turning ideas into reality for things related to automation, robotics, mechanical design, electronic design, prototyping, UI/UX design, desktop application, headless system, and other software development.