Creating a smart chatbot to motivate young adults to dispose of their plastic more responsibly

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ABSTRACT
Plastic pollution is a severe problem in the Netherlands, affecting not only the environment but also human health. People who do not properly dispose of their plastic, causing it to end up in inappropriate places, are one of the instigators. Plastic disposal can be a challenging operation because it requires sorting, cleaning, and removal. A data-driven chatbot and gamification methods based on psychological factors may offer a promising solution. It may gather the most intention for the desired behaviour by learning from the user and adjusting to the user. This study will look into the many ways that are required and explain why decisions were reached. To answer the core question and obtain input, multiple user testings are used. The proposed prototype intends to address the hurdles that prevent people from properly disposing of their plastic.

INTRODUCTION

In only one human lifetime, the annual global production of plastics has expanded dramatically. Plastic manufacturing has increased from 2 million tons in 1950 to an anticipated 600 million tons by 2025 (Plastic Soup Foundation, 2022). Plastics, also known as synthetic organic polymers, are very valuable materials because they are lightweight, affordable, robust, resistant, and easy to manufacture (Iacovidou, 2021). This results in its widespread application in several industries, including construction, electronics, packaging, and others (Iacovidou, 2021). Although plastics were first thought to be safe and inert, their abundance and whereabouts have caused several issues. The biggest one is plastic pollution, the disposal of plastic in the environment, which harms nature and its creatures (Okunola, Kehinde, Oluwaseun, & Olufiropo, 2019). However, toxicology expert Dick Vethaak (Plastic Soup Foundation, 2022) also notes that *"we are dealing with a human health issue as well."*

Plastic infiltration

Microplastics—minuscule fragments of plastic formed by the degradation of plastic garbage over time—were identified in human blood and lungs for the first time in March 2022, demonstrating that plastic particles can travel throughout the body and settle in organs, causing harm (Carrington, 2022). These negative consequences are most likely the result of microplastics carrying chemical additives, some of which have lately been linked to health risks (Plastic Soup Foundation, 2022). Microplastics & Health (Zonmw, 2021) discovered that high levels of microplastics in the body diminish cell viability and permeability. They have been observed in brain cell cultures to cross the blood-brain barrier and attach to immune cell communication. Microplastics have a negative influence on the lungs as well; they have been related to lung sickness and cause lungs to grow and heal more slowly. In addition, poor bowel function, inflammatory reactions, and immune cell encapsulation are all other concerning first results of microplastics entering the body (Zonmw, 2021).

Microplastics can enter the human body as a result of their presence in food. Microplastics can infiltrate the roots of various fruits and vegetables, such as apples, wheat, and lettuce, before going on to the edible parts of the plant (Plastic Soup Foundation, 2021). In addition to crops, microplastics have also been identified in pig and cow blood. These microplastics are unable to be broken down by the intestines and wind up in processed meat or manure (Ionescu, 2021). The University of Amsterdam corroborated this by discovering that plastic components were present in 80% of tested farm meat and dairy products (NOS, 2022). This is possible due to the presence of microplastics in agricultural irrigation runoff and/or sewage sludge used as fertiliser (Plastic Soup Foundation, 2021). Microplastics can enter these areas due to their transmission by rivers and wind (Plastic Soup Foundation, 2021). Prior to that, these microplastics could have come from a forgotten plastic bag on the side of the road, a bag that entered the environment as a result of improperly discarded plastic and or littering, initiating the plastic pollution process (Plastic Soup Foundation, 2022).

Target group

Some young individuals between the ages of 15 and 24 are said to replicate this polluting process more than others (Cheng, Koo, Mohd Nasir, & Wong, 2021). Young adults have generally shaped a "ecologically oriented" generation with the help of social media exposure and environmental education, which represents individuals with strong environmental views who enjoy engaging in environmentally good behaviours; however, not all young adults intend to act on that attitude (Calculli, D’Uggento, Labarile, & Ribecco, 2021). Unconcerned ecologists are young adults who have a high environmental ethic but have no intention of acting on it. (Calculli, D’Uggento, Labarile, & Ribecco, 2021) This is seen in their plastic disposal habits, with the average Dutch young adult disposing 5% of their plastic towards deposit, 37% into the appropriate container, and 58% elsewhere (Snijder, & Nusselder, 2019). When asked about their plastic-disposal habits, 28%

of Dutch young adults admit to occasionally throwing plastic debris in the improper area or container, and 93% report seeing their peers do the same (Snijder, & Nusselder, 2019).

Technical solutions

Many studies and prototypes have been developed in an attempt to improve how young adults approach plastic. With the help of an application, My Little Plastic Footprint, users may use less plastic by seeing their Plastic Mass Index—a gauge of how much plastic they contribute to pollution—and receiving advice on plastic alternatives (Plastic Soup Foundation, 2021). Governments themselves have also acted, such as the Netherlands, which began charging for the use of plastic bags and imposing a deposit on every sale of plastic bottles in 2021 (Plastic Soup Foundation, 2022). However, measures that try to keep the user from using plastic are often not successful, in the words of Trent Hodges, manager of plastic pollution at the Surfrider Foundation, *"it is so ubiquitous and such a common item, it becomes a force of habit"* (Smith, 2018). Other studies therefore concentrate on enhancing one's plastic disposal habits. A pledge system that awarded commitment for sustaining recycling behaviour was investigated by Wang & Katzev (1990), however it had no lasting impact. Lamata (2021) created a voice user interface application that connected with Google Assistant or Alexa, allowing users to show them a photo of their trash and receive advice on where to recycle it. This experiment was more effective as they valued the friendly interface that could assist them with the recycling procedure.

A chatbot is a technology that is noted for its friendliness and helpfulness (Adamopoulou, & Moussiades, 2020). Chatbots, also known as conversational bots, are computer programs that can respond to text or audio communications in order to aid the user in completing a common task (Adamopoulou, & Moussiades, 2020). These computers attempt to replicate human responses, and they can be programmed to alter and train their responses to match the user's preferences (Adamopoulou, & Moussiades, 2020). Thence, their adaptability may aid in accommodating young adults, all while assisting in the common task of disposing of plastic correctly and attempting to modify their plastic behaviour. As a result, the research question of this paper concludes: <u>How can a chatbot application motivate young adults to properly dispose of their plastic?</u>

THEORETICAL FRAMEWORK

Plastic types and their distinctions

Plastics are a broad category of material; there are several varieties of plastics depending on the components and production-related elements employed. They are polyethylene (PET), high density polyethylene (HDPE), polyvinyl chloride (PVC), low density polyethylene (LDPE), polypropylene (PP), polystyrene (PS), and polycarbonate (PC) (Okunola, Kehinde, Oluwaseun, & Oluwaseun, 2019). The majority of plastics are used for packaging, with building and construction, textiles, home products, and others trailing behind (Okunola, Kehinde, Oluwaseun, & Oluwaseun, 2019). The most common types of plastic are PET, which includes water bottles, jars, and sheets, HDPE, which includes bags, containers, and toys, LDPE, which includes bottles and tubes, and PP, which includes disposable cups and strays (Kumar, Samadder, Kumar, & Singh, 2018). Less frequent are PC, which contains CDs and helmets, PS, which includes glasses, trays, and cassette boxes, and PVC, which includes pipes and wires (Kumar, Samadder, Kumar, & Singh, 2018). The recyclability of plastics also varies; whilst HDPE may be easily recycled and repurposed as plastic bottles, jugs, toys, and furniture, PS is more difficult to recycle due to its toxicity (Alan, 2022). Next to PS, PET, PVC and PC also contain toxins that can be leaked, toxins such as antimony oxide, ethylene oxide and benzene (Alan, 2022). However, the most harmful chemicals, known as bisphenol A (BPA), are exclusively found in PVC and PC.

BPA is an industrial chemical with a phenolic structure that has been used to make many plastics and resins since the 1950s (Vandenberg, Hauser, Marcus, Olea, & Welshons, 2007). BPA is among other things used in the production of the inner linings for infant bottles, reusable water bottles, and food cans (Proshad, Kormoker, Islam, Haque, Rahman, & Mithu, 2017). BPA may enter the body in a number of ways. First, BPA molecules may leak from beverage and food containers into beverages and foods over time. The leaching process is accelerated by repeated cleaning of the containers and storage of polymer-degrading acidic or basic materials (Proshad, Kormoker, Islam, Haque, Rahman, & Mithu, 2017). Second, when BPA-containing plastics are left lying around or are not properly recycled, BPA can be released into rivers and wind through the breakdown process of plastic (Proshad, Kormoker, Islam, Haque, Rahman, & Mithu, 2017). They have been connected to health problems such as infertility, neurodevelopment disorders, and hormone-related malignancies because they have been shown to interact with oestrogen receptors (Vandenberg, Hauser, Marcus, Olea, & Welshons, 2007). As a result, it is critical to properly dispose of BPA-containing plastics.

Aside from dangerous substances, there are differences in where and how plastic types must be disposed between nations, regions, and municipalities (Ellis, Rorrer, Sullivan, Otto, McGeehan, Román-Leshkov et al., 2021). Each municipality in the Netherlands has its own plastic disposal guidelines because each can have a different waste treatment plant. Residents in Maastricht can deposit their unwashed plastics in containers located on a platform or in parks (Gemeente Maastricht, z.d.). In Rotterdam, plastics can be thrown in with the residual refuse because the AVR waste treatment plant includes a separation machine that can separate 80% of the plastic (Gemeente Rotterdam, z.d.). Residents in Almere receive their own plastic container, which is picked up every two weeks and preferably only receives clean plastic (Gemeente Almere, z.d.). Labelling the various plastic types becomes challenging as well, because many Dutch products do not share or indicate where to dispose of them (Stephenson, 2018). Due to these variances, different types of plastic become polluted when mixed with other or food waste in the rubbish bin, resulting in an incorrect method of disposing of one's plastic (Stephenson, 2018).

Factors that influence recycling behaviour

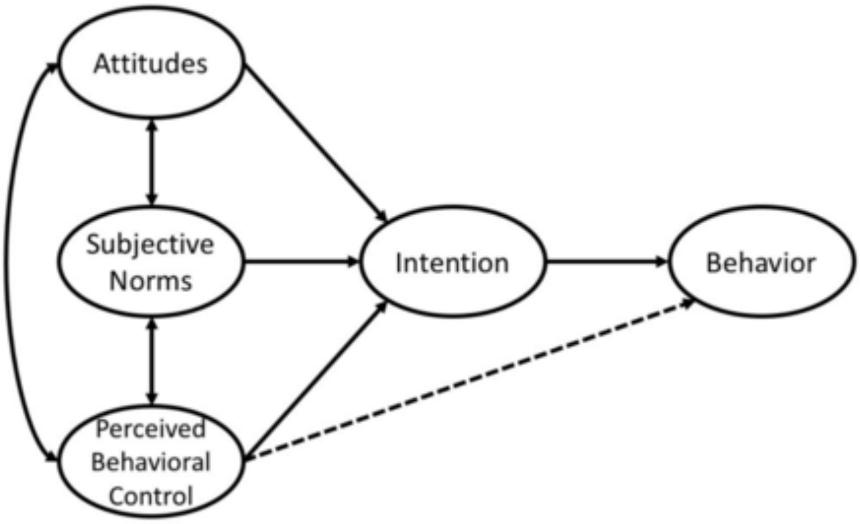
Many academic research have been conducted on the demographic factors that may lead to young adults becoming more actively interested in properly disposing of their plastic. Although Meyer's (2016) study discovered a positive association between education and discarding behaviour, some argue that this relationship is not causal because people may choose whether or not to utilise their education to manage their behaviour. This study supports the findings of De Silva and Pownall (2013) and Jones (1998), who identified no link between other demographic and environmental characteristics and plastic waste disposal behaviour. De Silva and Pownall (2013) find no evidence that wealth influences discarding behaviour, and Jones (1998) agrees, adding that there are no behavioural differences between cultures. Jones (1009) discovers, however, that minority groups have fewer pro-environmental attitudes and discarding behaviours. Nonetheless, Jones (1998), like the others, recognises that demographic factors have little bearing on the plastic behaviour system (Meyer, 2016; De Silva, & Pownall, 2013). De Silva and Pownall (2013) go even further, claiming that only human characteristics can influence plastic discarding behaviour.

Varotto and Spagnolli (2017) discovered 29 psychological and situational reasons why environmentally conscious people do not recycle or dispose of plastic responsibly, despite their concern for the environment and human health. According to their findings, the psychological factors of motivation, perceptions, social influence, and information and knowledge were deemed to be the primary reasons why people do not discard plastic properly (Varotto, & Spagnolli, 2017). Motivation looks at intrinsic and extrinsic motivation to recycle, whereas perceptions of recycling consequences entails information and beliefs about the consequences of not recycling. Social influence considers perceived support and pressure, opinions about other people's behaviour, and social comparisons. Last but not least, information and knowledge refers to knowing that a recycling program is in place or knowing what, where, when, and how to dispose of plastic (Varotto, & Spagnolli, 2017). Perrin and Barton (2001) concur, agreeing that lack of information, understanding, and motivation are major obstacles to recycling behaviour. They do, however, emphasise the need of focusing on a variety of factors rather than just one, as knowledge and information alone are unlikely to be sufficient to change one's behaviour (Perrin, & Barton, 2001).

Behaviour change strategies

Several approaches were devised to help push individuals in their trash discarding behaviour, with the "foot in the door strategy" being one of the most well-known (Burn, 1991). The "foot-in-the-door" influence approach, which has been successfully tried in the recycling industry, is one well-documented strategy for enhancing a behaviour modification that can urge someone to improve their discarding habits (Burn, 1991). This strategy requires the person to initially engage in a simple, "low-cost" behaviour before being asked to engage in more difficult, related behaviours (Burn, 1991). Using this method, the Tropaverde web platform encourages correctly plastic discarding and environmental stewardship among its users (Gibovic, & Bikfalvi, 2021). This is accomplished by giving them little tasks to do first in exchange for a reward, followed by greater duties (Gibovic, & Bikfalvi, 2021). Despite being effective, the strategy primarily focuses on large-scale groups and does not consider the individual's personal factors (Burn, 1991). According to Juliana, Lada, Chekima and Abdul (2022), discarding plastic is an activity that calls for a lot of personal work from the individual since they must sift, prep, and store the plastic trash, with each step varying in difficulty depending on the individual. It will be necessary to take into account a number of aspects in order to gather the most intention for them to do the recommended behaviour (Juliana, Lada, Chekima and Abdul (2022).

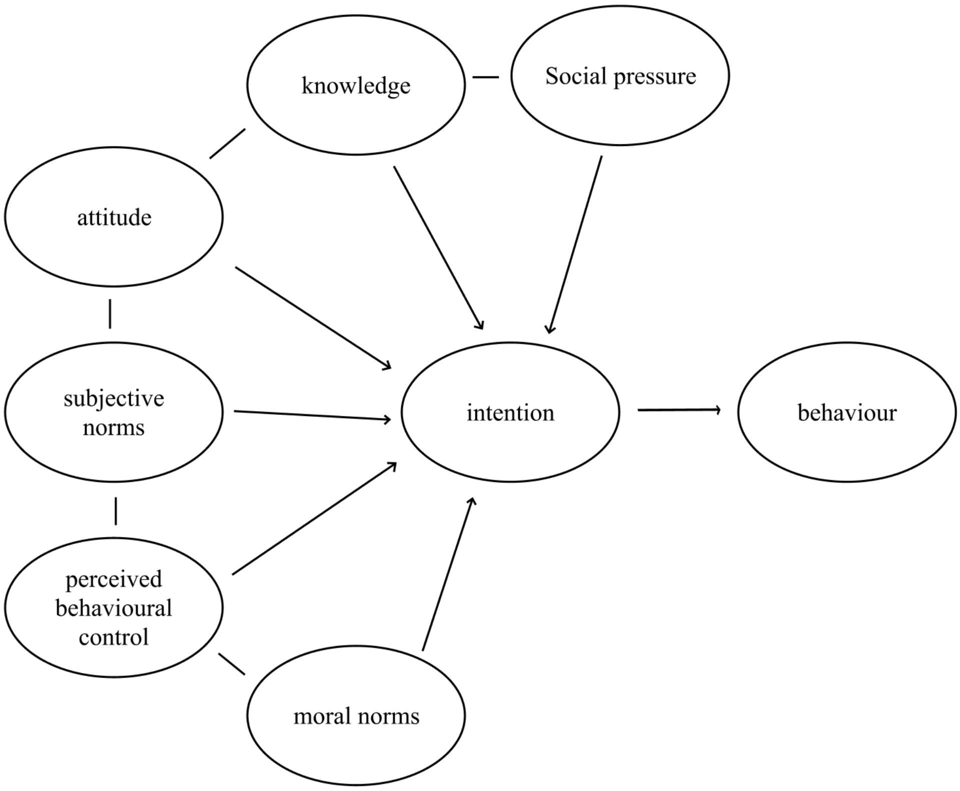
The theory of planned behaviour (TPB), a well-known methodology with roots in social psychology, has garnered recognition for its ability to explain and forecast the likelihood of recommended behaviour occurring (Aboelmaged, 2021). This theory's key component is behavioural intention, and behavioural intention can be reached when three determinants that comprise the theory can shape the intention: (1) the individual's attitude, which indicates whether they view the intended behaviour as favourable or unfavourable; (2) subjective norms, which demonstrate other people's opinions regarding whether the individual should carry out the intended behaviour; and (3) perceived behavioural control, which reflects whether they believe the targeted behaviour will be easy or difficult to execute (Aboelmaged, 2021). This theory explains how people respond in a variety of settings, circumstances, and situations (Aboelmaged, 2021). By using TPB one can learn to understand the key determinants of plastic discarding behaviour amongst young adults. Furthermore, each determinant can reveal where barriers exist and which one can best support behaviour change (Aboelmaged, 2021).



Combining theory and recycling variables

Numerous academics have applied the theory in a range of domains, including environmental studies, technology, health, and education; nonetheless, there are just a few specific studies that look into plastic discarding behaviour with TPB (Kumar, 2019). Hua and Wang (2019) demonstrated that TPB structures successfully predict consumers' proclivity to buy energy-efficient equipment in real-world scenarios. Furthermore, Sawang and Kivits (2014) discovered that subjective norms, environmental views, and perceived green preparation influenced managers' decisions to pursue green human resource initiatives. When it comes to plastic discarding behaviour, Ernst, Blood and Beery's (2015) recycling study demonstrates that student attitudes do not significantly predict intention toward environmental action, underlining that other external factors influenced the relationship between intention and recommended behaviour more. This belief is shared by Tonglet, Phillips and Read (2004), who believe that in order to explain recycling behaviour, additional variables such as personality, prior experiences, and traits should be incorporated in the theory as well.

TPB allows for the inclusion of extra variables, provided that these variables contribute significantly to the model's explanation of behaviour (Dorina, Mullan, & Novoradovskaya, 2021). Several attempts in the recycling area have been made to adapt, modify, and improve the model in order to increase its predictive value (Heidbreder, Bablok, Drews, & Menzel, 2019; Kumar, 2019). Moral standards, according to Onwezen, Antonides and Bartels (2013), can instill feelings of pride and regret in people. De Young (1985) concurs, noting that the individual would feel good after doing the required behaviour since they would feel like they had helped the environment and society, and guilty if they did not. Moral norms may so influence intention. It has also been discovered that having a thorough understanding and awareness of the consequences of plastic waste is associated with appropriately disposing of plastic (Juliana, Lada, Chekima, & Abdul, 2022). Understanding and awareness enable a person to examine their own behaviour (Juliana, Lada, Chekima, & Abdul, 2022). Awareness of the issues may thus improve influence to participate in correctly discarding behaviours. Thus, this study will incorporate the additional factors of moral norms and awareness, in addition to the previously mentioned knowledge and social pressure obstacles. As a result, the model should be able to reliably predict young individuals' intentions to discard plastic, hence assisting in the adoption of the recommended behaviour.



Personalised gamification

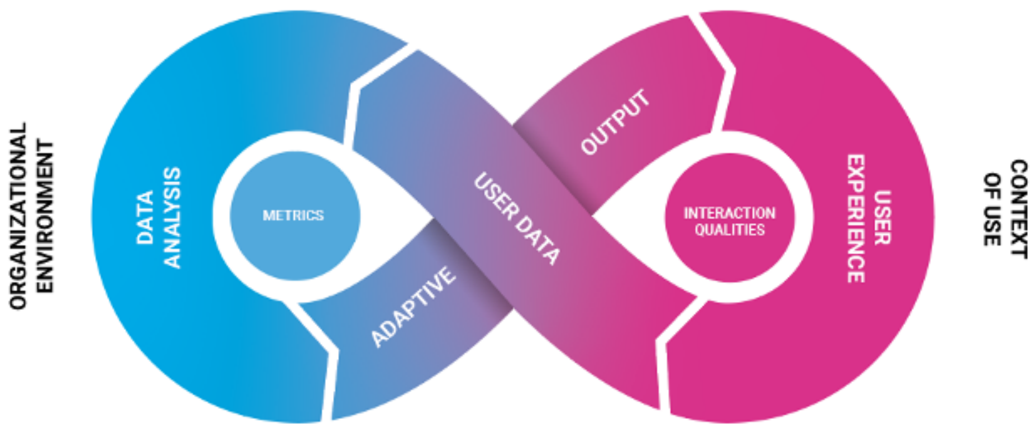
Gamified learning, often known as gamification, is an efficient method of communicating TPB concepts. Gamification is the process of applying game mechanics or game strategies, such as challenges, storylines, leaderboards, awards, badges, teams, points, win-state, and others, to achieve objectives and enhance overall motivation (Hamari, 2019). Due to its diverse components and applications, gamification has been applied successfully in a wide range of fields, including healthcare, business, and even recycling (Hamari, 2019). Specific game mechanics can assist drawing attention to a TPB aspect. This was discovered in Aldemir, Celik and Kaplan's (2018) study, which investigated the impact of particular game mechanics on factors such as self-evaluation, information collection, emotion-arousal, self-assessment, and other feedbacks. The findings reveal that learning material through a narrative game mechanic is the most successful. As a narrative can provide a meaningful story or context, it can help the user become engrossed in the material (Aldemir, Celik, & Kaplan, 2018). The game mechanic leaderboards can help trigger the TPB element subjective norms because they show the user that other people are doing the required behaviour, which can increase reputation, social pressure, and engagement (Aldemir, Celik, & Kaplan, 2018). Figure below depicts more gamification and TPB element relationships (Aldemir, Celik, & Kaplan, 2018). However, it is critical not to overwhelm the user with too many game mechanics, as this might become distracting.

TPB element	**Gamification method**	**Why?**
Attitude	Points	Points are able to give based evaluation. Points are considered very visible objects, and can be distributed from all kinds of activities. Points can also be considered as grades.
Subjective norms	Leaderboard	Leaderboards can create a competitive environment. Leaderboards offer participants a way to make reputation, which is able to raise social pressure ad participation.
Perceived behavioural control	Badges	Badges generate fun and a confidence boost. Badges can provide feedback on the basis of the participants performances. This helps participate self-asses their weekly achievements.
Knowledge	Narrative	Narrative is a dynamic elements that is able to present a meaningful story or context for the participant, instead of a plain text. Narrative can help users immerse themselves into the process and its knowledge.
Social pressure	Teams	Teams support community building. The community building process if affected by the interaction, relationship and pressure between teammates, implying that good communications facilities community building.
Moral norms	Rewards	Rewards are inexpensive objects with high sentimental value. Rewards are needed to be given continuously and systematically for to not lose disengagement.

To avoid overwhelming the user with gamification mechanics, the appropriate game mechanic must be picked for them. The Lambert, Solem, Zadrozny and Boehm (2021) research provides a similar illustration, and solution, of this. In a classroom, teachers gave the same bulk of materials to all of their students, but not all of them responded to it in the same way. With the aid of a variety of factors, they changed the curriculum to make it more personalised in order to get the best outcomes possible from all students. They first tailored the context to the student's interests, then they examined the student's attitude toward several sub-areas, and last they gathered the student's thoughts on how they would approach the subject in real-world situations. In the end, they made use of the student data and chose individual customised content, resulting in more motivation, involvement and more participation in the wanted class behaviour (Larsen, Solem, Zardozny, & Boehm, 2021).

Training the chatbot

A data-driven feedback loop might be considered when thinking of using user data to learn and improve the user experience and content. Data is a language made up of zeros and ones that, when translated, can be converted into information (Nguyen, 2021). That information can be transformed into knowledge and wisdom by analysing it and drawing conclusions. The more knowledge and wisdom amassed, the more accurate predictions of user data can be generated (Nguyen, 2021). After developing predictions based on the data, an adaptive output can be produced to improve the user experience (Nguyen, 2021). Continuously doing this is referred to be a data-driven feedback loop. It can combine new data from archives or online measurements of actual systems in real time, resulting in more accurate analyses, predictions, controls, and results (Huang, Lei, Jiao, & Zhong, 2021). In essence, it learns from users and modifies to fulfil their needs, thereby training itself. The prototype retains higher efficiency the more trained it is.



A technology that is able to train itself, collect data and focus on user experience is called a chatbot. Chatbots are well-known for their "information-gathering tool" and quick and easy responses (Adamopoulou, Moussiades, 2020). Chatbots are also quite popular, as they are employed in a variety of industries such as education, customer service, healthcare, robotics, and industrial instances (Adamopoulou, Moussiades, 2020). They became so popular due to their communicative dependability, quick and simple development iterations, and low design efforts (Adamopoulou, Moussiades, 2020). Many services, such as payment services, can be linked within the chatbot, making it a platform-independent technology capable of simply transferring data across itself

(Adamopoulou, Moussiades, 2020). However, some users continue to have poor interactions with chatbots, leading to resistance to the technology. Despite their advancement, some say that chatbots have become masters of deceit due to their human-like qualities and concealed techniques, creating an uneasy sensation for the user (Adamopoulou, Moussiades, 2020). Furthermore, chatbots frequently fail to recognise the user's goal or personality, which can lead to irritation (Adamopoulou, Moussiades, 2020). To boot, standard chatbots have limited responses, making it impossible for them to answer multi-part queries or respond in a more personal manner (Adamopoulou, Moussiades, 2020).

Standard chatbots, also known as rule-based chatbots, are constrained by the fact that they must adhere to a specified set of rules, whereas AI chatbots are more complex and flexible in their service (Haristiani, 2019). The launch of the Facebook Messenger chatbot in 2016 is an example of this (Veglis, & Maniou, 2019). The chatbot learned about the user's interests and behaviour via their messages and language. As it became more sophisticated and accurate, the chatbot could alter its responses to the user and give suggestions, such as if the user wanted to attend a specific event (Veglis, & Maniou, 2019). To accomplish this level of personalisation, the chatbot must work with a natural language processing (NLP) module (Channel, Yuying, Yuji, Razaque, & Yang, 2018). The NLP module can help validate user-provided data by doing sentiment analysis on the supplied text. It will then instruct the knowledge base on how to respond to the outcomes (Channel, Yuying, Yuji, Razaque, & Yang, 2018). The strategy used by the NLP module has several advantages, including the capacity to improve loyalty, make conversations more engaging, and make the chatbot more desirable (Haristiani, 2019). When employing NLP, certain disadvantages must be considered. The module must be thoroughly trained before it can produce accurate results (Haristiani, 2019). It may also take some time for the user to build up trust, and if foul language was used, the module may learn offensive keywords inadvertently (Haristiani, 2019).

Communicating to influence behaviour change

It is critical for the chatbot to utilize a directive communicative technique in order to guide the user to behavior change. This may be found in Cacanindin’s (2020) Behaviour Change Agent Framework (BCAF), where the AI chatbot functions as a personal counsellor, motivating participation change and self-efficacy. To achieve the behavior modification aim, BCAF is divided into five stages, each of which can be adjusted to include TPB parts of this project. The first step is known as pre-contemplation, and it focuses on greeting the user and discussing the general problem or their problem behavior. The second phase is reflection, in which the user may begin to consider how to change as a result of step one. As a result, the chatbot will focus on self-evaluation questions to acquire information about the user. The third step is preparation, in which the chatbot helps the user believe in one's ability to change and make commitments by providing knowledge or helpful links. The fourth step is action, in which the chatbot asks questions to elicit the activities that the user intends to take. The next step is maintenance, during which the chatbot may incorporate stimulus controls to prevent the user from reverting to previous behaviour (Cacanindin, 2020).

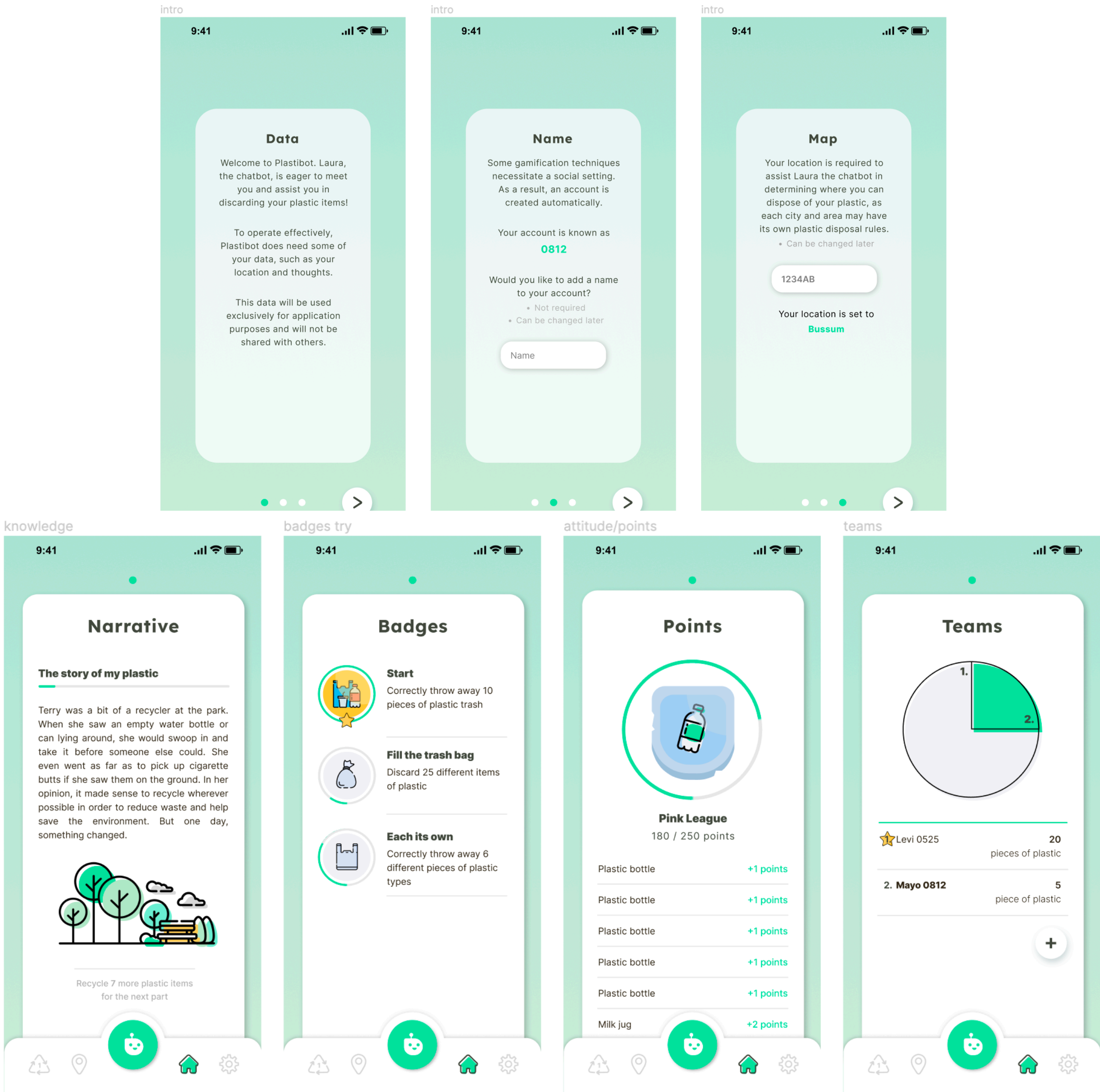
METHODOLOGY

This is a user-centered, applied research study aimed at developing a data-driven solution to motivate young adults to properly dispose of their plastic. To investigate the study question, user testing, data analysis, and iterations are used.

Prototype explanation

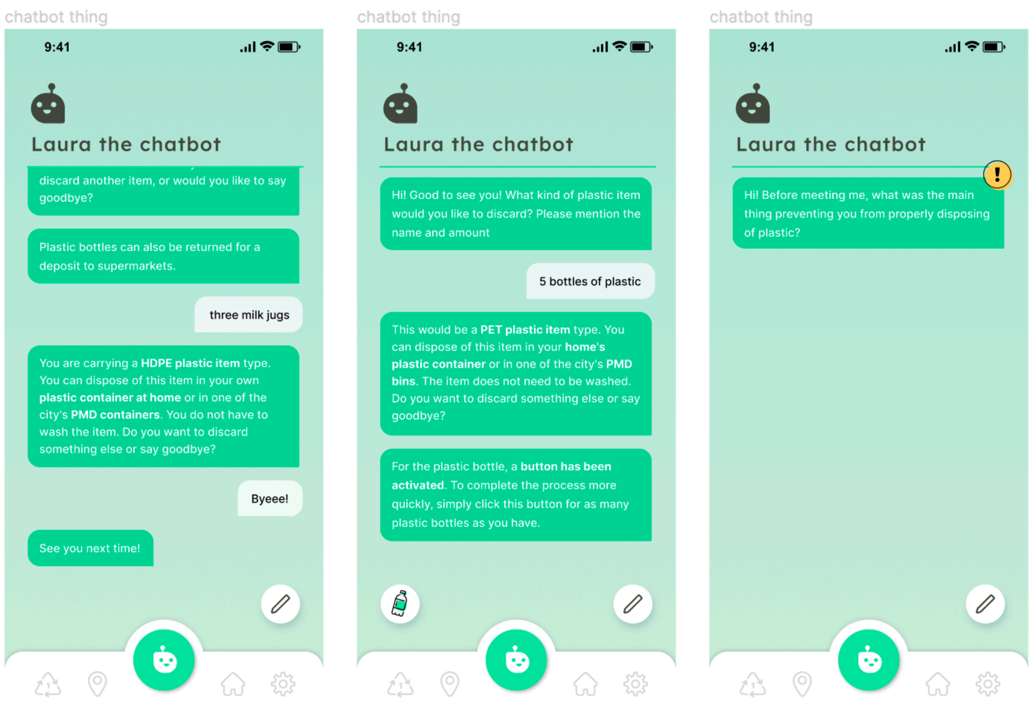
This study used an action research approach, which included an iterative process that resulted in the creation of a data-driven chatbot prototype. The chatbot provides young adults with personalised gamification methods to motivate them to properly dispose of their plastic. The prototype has four iterations and is programmed in Visual Studio Code and designed in Figma. The prototype can be interacted with via smartphone. The prototype listens to the user and analyses the data they provide. The analysis improves with each iteration, and the chatbot can provide an even better user experience. This user experience consists of presenting the correct content and, if necessary, assisting the user in speeding up the procedure.

A welcome screen will appear when the user first launches the application. This welcome message informs the user of the program's goal, gives the user an automated account and requests permission to use their data for the application. They return to the home screen after submitting. The home screen can accommodate gamification methods such as points, leaderboards, badges, story, teams, and rewards. These gamification techniques are based on TPB elements attitude, subjective norms, perceived control, knowledge, social pressure and moral norms. Each method captures a TPB aspect and motivates the user in their own unique way. Based on the user data, the chatbot can assist in determining which gamification strategy will work best for them. Data must be provided to the chatbot in order for a gamification approach to be activated.

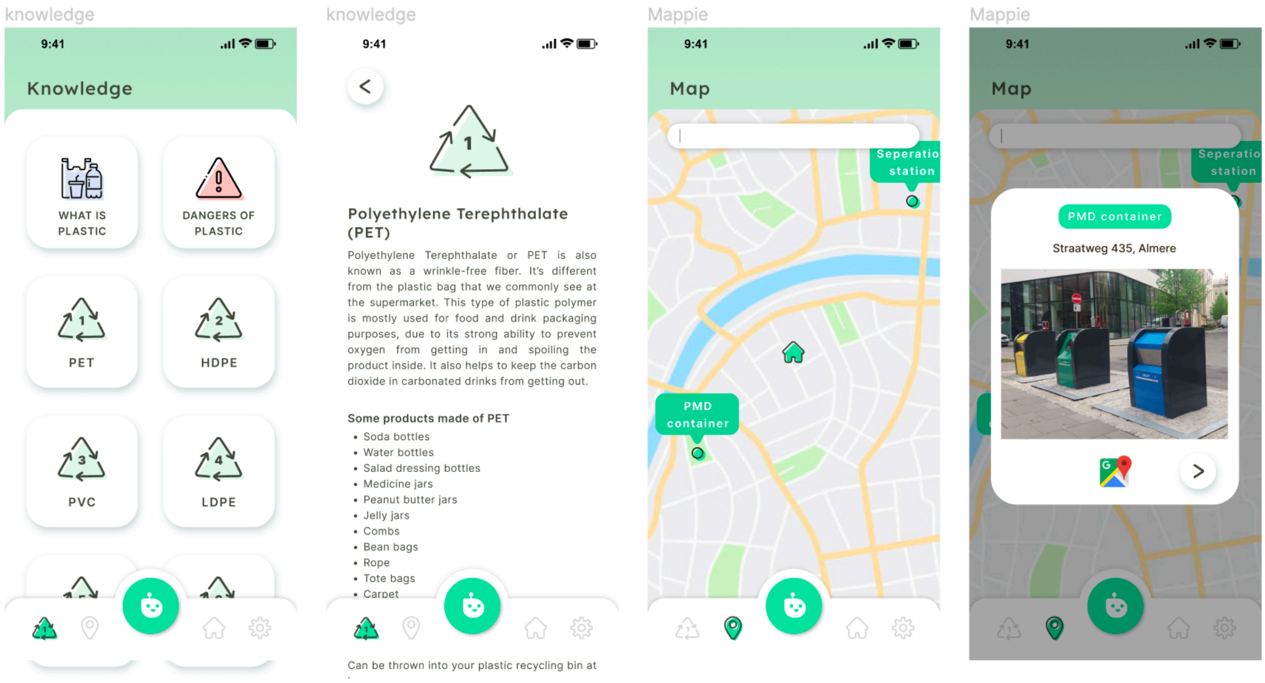


Personalisation is included in the application's core feature, the chatbot. Because the chatbot is built with an NLP module, it can personalise the user's experience by learning from their data. The chatbot serves two purposes. First, it assists the user with the common chore of disposing of plastic. A brief dialogue in which the user informs the chatbot what item they have and the chatbot responds with where they should discard it correctly. The chatbot maintains track of the plastic items discarded by the user, and when a large volume of an item is identified, a button appears. For instance, if the chatbot recognises that the user throws away a lot of plastic bottles, it will add a "plastic bottle" button to the chatbot screen. When the user clicks the button, they can bypass the talking process and quickly inform the chatbot that they will discard a plastic bottle. This expedites the procedure and improves the user experience.

Second, a notification may appear informing the user that the chatbot want to converse. The chatbot will offer a personal question when you enter the chat, such as "What inspires you to properly dispose of your plastic?" or "Before meeting me, what was the major thing keeping you from properly disposing of plastic?". These questions are inspired by the Behaviour Change Agent Framework rules. The answers to these questions can tell the chatbot which TPB elements would be most effective as an incentive for them. For instance, if the user responds, "I did it because I felt pressure from friends," the TPB element "social pressure" is linked and the gamification method "Teams" is activated. The chatbot offers a data-driven feedback loop in this manner. It performs analysis and provides an adaptive output to improve the user experience by analysing user data.



An information screen is also available in the application, which helps highlight the differences in plastic types, as well as the toxic compounds they can contain and the effects they can cause. A map screen is provided to assist the user in determining where they should dispose of their plastic, as each city in the Netherlands has different requirements. The user can discover more about PMD containers, separation stations, and plastic laws on their particular street by clicking on the available locations on the map. Finally, if the user wishes to change anything, such as their location, a settings screen is provided.



Sampling strategy - population of interest

The population of interest for this research project was young adults aged 15 to 24 who live in the Netherlands and do not follow proper plastic disposal guidelines. They do not have to be Dutch nationals, but they must live in the Netherlands and be familiar with the local laws. Participants were chosen from the HU University of Applied Sciences or the Amsterdam University of Applied Sciences.

Sampling strategy - sampling method

Participants were recruited on a volunteer-basis. Participants were discovered by asking about at the HU University of Applied Sciences and the Amsterdam University of Applied Sciences. They were then asked about their age, their plastic discarding habits, and whether they wanted to participate in the study.

Sampling strategy - sample size

A total of 7 people agreed to test the prototype. All 7 were in the age range, with four indicating they do not know their city's plastic guidelines and thus dump plastic in their usual bin, and three saying they try to dispose plastic correctly but do not put much effort into it. Each participant was asked whether they wanted to test in multiple iteration cycles; this invitation was optional, although some individuals agreed to participate in more rounds. The majority of the tests were conducted at a university, with a few conducted through Microsoft Teams.

Sampling strategy - data management

All participants were asked for their consent to participate in the research tests. They were informed that their data would only be utilised to enhance the prototype and that their information would be kept private. They were promised that all names would be anonymised in order to safeguard their identities and that the project would never be published. This adage was repeated at each test.

Data collecting

Before the chatbot can train and work, data must be collected. Chatbots employ a script, which assists the chatbot in determining how to respond to the user. This prototype's script is made up of "tags", "patterns", and "responses". A tag identifies the topic of the discourse. The tags in this project are about the plastic disposing process and the TPB elements. As a result, tags such as "PET plastic item" exist if the chatbot and user are discussing a plastic bottle that needs to be discarded, while tags such as "knowledge" exist if the chatbot is asking personal questions and a knowledge answer is provided. For example, if a user says "I want to learn," the "knowledge" tag is triggered, and the chatbot selects an answer from that tag.

Each tag contains numerous responses, each response is a different way for the chatbot to respond to the user's "I want to learn" request. In this scenario, the responses could be "Thank you for you honesty, I will take this into mind." "I agree with you, knowledge is very important, so I will activate the narrative package for you," and/or "That is a brilliant way of thinking, thank you for sharing. I'll turn on the narrative package for you." One response is created at random and returned to the user.

Finally, there are patterns, which are derived from user data. Patterns are words or sentences that a user could say to cause a tag to be triggered. For example, the patterns in the tag knowledge could include "education", "knowledge", "learning", "learn", "reading", "understanding", "knowing" and "know". When the user enters "I want to learn," it recognises the term “learn” and navigates to the appropriate tag. As the patterns are created from user input data, they improve in terms of word count and size with each iteration. Patterns relating to the target group were generated through observations and discussions with participants. Many participants used the words "plastic pollution" and/or "environment" when discussing knowledge, indicating that they want to learn more about those subjects. Some participants used terms like "becoming wise," "top tier knowledge," and "wizard brain" to describe their experiences. The better the chatbot can recognise patterns and appropriately identify them by learning how the target group speaks and writes. By learning how the target group speaks and writes, the better the chatbot can recognise the pattern and place it with the correct tag.

```
{
  "tag": "knowledge",
  "patterns": [
      "Education",
      "Knowledge",
      "Learning",
      "Learn",
      "Reading",
      "Understanding",
      "Knowing",
      "Know",
      "Plastic pollution",
      "Environment",
      "Becoming wise",
      "Top tier knowledge",
      "Wizard brain"
  ],
  "responses": [
    "Thank you for you honesty, I will take this into mind.",
    "I agree with you, knowledge is very important, so I will activate the narrative package for you",
    "That is a brilliant way of thinking, thank you for sharing. I'll turn on the narrative package for you."
  ]
}
```

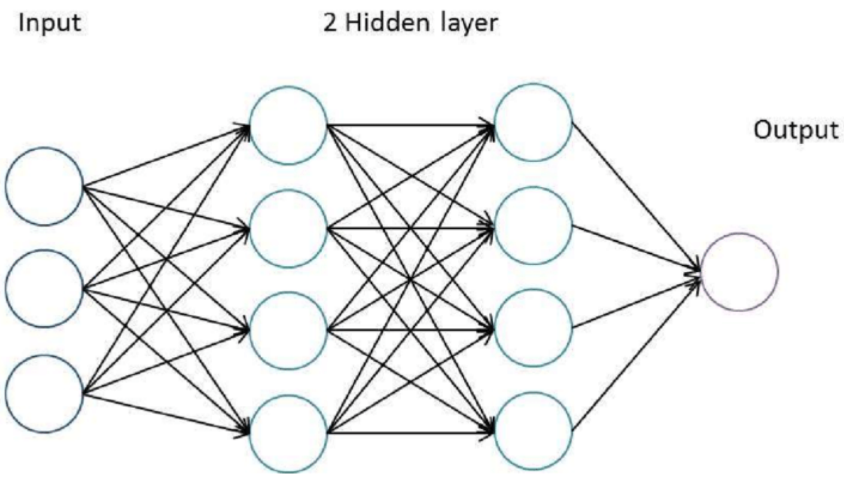
Data cleaning

It is now time for the chatbot to read the json file. However, because text (strings) is difficult for a chatbot to process, the json file must be converted to numbers (integers). This is possible with the procedure bag of words, which consists of four steps (Loeber, 2020). Tokenisation is the first phase, in which each string is collected and organised into an empty list (array). The second phase is lowering and deleting, in which each string is lowercased and punctuation marks are eliminated.

Third, stemming removes suffices from words and standardises them to their fundamental stem, eliminating the need for the machine to learn all of the numerous variants of a word. Finally, bag of words evaluates the array as a collection of words and then determines whether or not there is a match with a pattern for each individually. The chatbot can now read the json file.

Data training

The chatbot can now be trained after the file has been read. It is vital for the chatbot to train since the more training it receives, the more likely it is that the chatbot will recognise the pattern and associate it with a tag. The chatbot is trained using a Feed Forward Neural Net (FNN), which is a network in which data flows from an input layer via a hidden layer to an output layer that makes a prediction (Sharma, 2022). The quantity of training can be determined by epochs; one epoch signifies that the training dataset has been processed by the FNN once (Brownlee, 2022). Loss, which might be described as errors, can also give information about the training. If the loss is high, it indicates that the workout is difficult (Stack Overflow, 2016). The greater the number of epochs, the lower the loss, the greater the likelihood of recognising a pattern, and the better the training. This project employs 2000 epochs with a general loss of 0.0003.



Now that the chatbot is functioning properly and efficiently, it will continuously examine the user input data for patterns that link to plastic products or TPB element tags. The chatbot will remember each plastic item tossed so that the skip buttons for the highest plastic items can be created. The chatbot will also recall words said in TPB considered tags, and if they are mentioned a few times, a gamification method will be activated.

RESULTS

This iteration was completed by four students: 23 female, 23 male, 24 female, and 21 female.

How accurate was the chatbot in identifying user patterns?

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**
Identified pattern correctly	Around 30%	Around 20%	Around 50%	Around 90%
Identified pattern incorrectly	Around 50%	Around 70%	Around 30%	Around 1%
Could not understand pattern	Around 20%	Around 10%	Around 20%	Around 9%

The chatbot's operations are the first outcomes that may be viewed. Each iteration examined the chatbot's responses and if it was able to correctly recognise the pattern from the user input data. Iteration 1 contained a modest json file, but the chatbot still had trouble finding patterns. The main flaw in this json file appeared to be that there were too many patterns that had the same terms. "My motivation is attitude," or "My motivation is information," for example. Both patterns had a high likelihood if the phrases "My motivation is" were used, therefore it frequently chose the incorrect pattern. Iteration 2 was a json file with many more tags, patterns, and lengthier sentences overall. Due to the larger phrases, many little words such as "this," "that," and "I" would reoccur in a variety of patterns. Iteration 3 deleted these small words, resulting in strange sentences, yet it proved to be more effective. Finally, iteration 4 included a new strategy that involved leveraging the participants' vocabulary and breaking down big statements into little terms. If only one word were recognised, the correct pattern would emerge. Using this strategy helped the conversation flow during the testing phases, making the prototype feel more real and satisfying.

What gamification method did the participants get

	Iteration 2	Iteration 3	Iteration 4
Attitude	0	0	0
Subjective norms	0	0	1
Perceived behavioural control	0	1	0
Knowledge	1	1	1
Social pressure	1	1	1
Moral norms	2	2	1

The TPB elements produced various interesting results, as seen in the table above. Each participant was asked to explain what motivates them the most from iteration 2 to iteration 4. Moral norms, societal pressure, and knowledge were the most frequently mentioned, while subjective norms and perceived control were only mentioned once. There were no votes for Attitude.

How likely is it that this gamification method will motivate you, rate each on scale from 1-5

	Attitude	Subjective norms	Perceived behavioural control	Knowledge	Social pressure	Moral norms
Total	12	18	20	17	23	27
Mean	3,29	2,57	2,86	2,43	3,29	3,86

Furthermore, each participant (7) was asked to rate on a scale of 1-5 how likely this TPB aspect would motivate them to engage in proper plastic disposal behaviour. Moral norms, the feelings of pride and remorse while disposing of rubbish, came out on top. This can be observed in many of the iterations, as when questioned how they felt after doing this they answered with the likes of "I feel good" or "I felt like a did a good thing". Both social pressure and perceived control are characteristics of being pressured from others. This was also a recurring event in iterations, as participants expressed a preference to do it together with a friend. With consistent numbers, perceived control and knowledge follow. Finally, none of the participants appear to be influenced by their attitude.

Another interesting finding is that the behavioural intention model was not well received by participants. Following the 5-step approach upset them more than it motivated them. Even though it was only a one-time activity, answering 5 questions back to back sucked the pleasure out of it. It also slowed down the plastic disposal procedure, and having to answer a question each time someone discarded an item became tiresome. They wanted the process to be as rapid as possible because it would have to be repeated many times. The look and feel of the prototype helped the participants regain their vitality. Many participants commented positively on the application's colourful and light appearance, which made them want to open it again. Participants frequently used the map tool to see where they might dispose of their plastic products. The information screen was also visited, and several insightful remarks were made about how they had learnt something new. The plastic bottle button, which activated once a certain number of plastic bottles were discarded, was also well welcomed. Anything that could be done to expedite the process was greatly appreciated. Finally, several intriguing questions were raised. As one participant considered plastic in general as a poor use, they questioned the prototype's goal: "Does this not stimulate plastic use?" and "The gamification methods motivate the buying of plastic."

DISCUSSION

The motivation to purchase plastic items in order to use them in gamification methods may not be a negative thing. The plastic would not damage anyone if the target group disposed of it properly. This notion may also appeal to other stakeholders, such as a supermarket. The prototype aids in the promotion of plastic goods, resulting in increased revenue for them. Other stakeholders, such as women who want to become pregnant, will benefit from having less plastic in their food, lowering their chances of infertility. The quantity of plastic is not the issue; it is their location. As a result, this prototype is solely concerned with the problem.

The TPB elements' outcomes are a critical determinant in combating the problem. The results, as researched, would not totally coincide with the normal TPB elements, as they would have overlooked some parts that are essential for recycling. Subjective norms and perceived behavioural control were well welcomed, but did not appear to be a primary predictor in influencing the desired behaviour. This contradicts Sawang and Kivits' (2014) study, which stated that subjective norms were a major factor. Attitude was not well welcomed, which is consistent with Ernst, Blood and

Beery’s (2015) recycling study, which yielded similar outcomes. This calls into question the validity of the TPB theory, as the three determinants that comprise the theory failed to impact the desired behaviour. The claim that TPB can be applied in a variety of domains is dubious. However, by incorporating recycling-based aspects, a significant determinant could be discovered. Onwezen, Antonides and Bartels (2013) and De Young (1985) both spoke about the relevance of moral norms, which is reflected in the study's findings. Social pressure and knowledge also appeared to provide the user some intention, which is consistent with the findings of Varotto and Spagnolli’s (2017) study. By breaking down the obstacles, more room for intention can be created.

The chatbot has shown to be an excellent tool for acquiring information. An intriguing combination was made by combining a smart chatbot with a data-driven feedback loop. The chatbot was constantly interacting with the user in order to improve their user experience. However, some contradictory data did emerge. For the chatbot to induce behaviour modification, a five-step method was advised. The user's intention would be gained by guiding them through these phases. However, the results suggest that this was usually met with dissatisfaction because it took so long and they just wanted to throw away their plastic. As a result of this research, it is clear that applying the same chatbot rules to every chatbot would not work. To match the needs of the target group, the chatbot's rules must be tailored towards them.

This study is unique in its approach to the problem of plastic disposal in young adults. It used a smart chatbot that was constantly training itself and was tested in a real-world working environment with users. The study is the first to integrate its own customised TPB methodology with gamification techniques. The study opens the door for future research to investigate the application and learn from its key determinants.

CONCLUSION

This study explored how a prototype might be trained using user data to help convince the target group to dispose of their plastic more responsibly. The research question, "How can a chatbot application motivate young adults to properly dispose of their plastic?" can be answered positively. The study explored new areas, yielding solutions and answers that were previously unavailable. The investigation produced novel and intriguing findings. Moral norms appeared to be the most important main determinant in influencing desired behaviour, followed by pressure from society, family, and friends. The chatbot was able to successfully assist the user in disposing of their plastic while also learning more about them. The data-driven feedback loop proved to be the application's core, making it a unique and enjoyable experience for the user. The study was thus able to provide a fresh perspective on how to develop a creative solution for a pretty mundane routine chore, all while keeping the overall goal of decreasing the problem in mind.

LIMITATIONS & FUTURE RESEARCH

This study has limitations that may have an impact on the results. First, each test with a participant lasted approximately fifteen minutes, which is insufficient time to assess whether the gamification method was truly beneficial. This might be accomplished more effectively through long-term testing, in which the user would test the program for a week and then evaluate the gamification outcomes. Second, because the project was only evaluated with seven participants, this study does not have a large sample size. A broader breadth of user testing can aid in the validation of results and conclusions. Third, this study did not consider whether people can perform waste separation at home. As a result, the ease of plastic discarding behaviour is not well thought out. All of the limitations described above leave room for future research on the subject. Future research could also look into how the data-driven part of the program can be taken even further, improving personalisation and therefore intention. Finally, the application is readily built so that it could easily add new types of waste and where they should go. This could be an intriguing aspect, as some waste separations may necessitate more work and motivation than others.

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