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Integrating Ai And Microbial Biodegradation For Sustainable Solutions To Plastic Pollution

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ABSTRACT:

Introduction/Importance of Study: Pollution by plastics is a rapidly rising problem in the world, and conventional approaches to waste disposal are not effective. Another issue is to find new ways how to address the increase in the quantities of plastic in ecosystems.

Novelty Statement: This research examines the coupling of artificial intelligence with microbial biodegradation, thus offering new concepts for optimizing plastics biodegradation solutions.

Material and Methods: The use of artificial intelligence was applied in determining the relative efficiency of microbial strains, and enzymes used in the degradation of plastic. AI's applications were examined for the ability to review cases and experimental data regarding the predictability of best conditions for biodegradation and the enhancement of microbial activity.

Results and Discussion: AI was very effective in not only identifying and enhancing the microbial strains for degrading plastics but also in enhancing the economy. Est deposited for specific key case examined how AI tools enhance enzyme activity, strain identification, and ways to adapt to the environment; this gave more impetus to touch with scalability and prospects for industrial use.

Conclusion: The application of AI in microbial biodegradation shifts the current management techniques from volumetric, energy, and resource–consuming present options to ecological and efficient models with huge potential to reduce the environmental degradation of plastics.
KEYWORDS: Plastic pollution, Artificial intelligence (AI), Microbial biodegradation, Sustainability, Waste management, Environmental degradation, Optimizing biodegradation, Novel solutions, Enzymes, Eco-friendly technology.

INTRODUCTION:

Plastic waste is a global extraverted emergency and complex socio-environmental problem that merits an increase in global concern as they continue to accumulate millions of tons of plastic waste are dumped in landfills, oceans, rivers, and other environments around the globe. For this reason, environmentalist argues that plastics are dangerous since their decomposition is very slow thus resulting in a global issue as plastics affect marine life, and ecosystems and are likely to affect human life in the long run. In the last few decades, there has been a sharp increase in the production of plastics, owing to enhancements in consumer use and industrial employees using plastic products. Modern methods of waste disposal such as collection and sorting for recycling, landfilling, and incineration have proven to be ineffective in managing today's overwhelming plastic waste. Recycling especially is affected by challenges such as logistics, insufficient structures, and contamination which lead to low recycling rates in the world. Therefore, there is a need for new and proper measures that can help reduce cases of the effects of plastic pollution (Mohanty, Maharana, & Pandey, 2024) (Anitha, Maruthi, & Sudha, 2022).

An area that currently appears to be receiving much attention in its research is microbial biodegradation, whereby microorganisms including bacteria and fungi can directly decompose plastics into simpler unwanted compounds. This biological approach looks like a sustainable solution if only considering some microorganisms that were found to possess the ability to break down plastics including polyethylene terephthalate (PET), polylactic acid (PLA), and more. However, there are several constraints to the practical application of microbial biodegradation such as slow rates of degradation, the requirement of specific conditions to carry out the process, and identification of efficient microbial strains. The latter has partly limited microbial biodegradation applicability from industrial and environmental viewpoints, pointing to the fact that more progress is desirable in this sphere (Devgan, Singh, Pandey, & Mathur, 2024) (Maraveas, Kotzabasaki, & Bartzanas, 2023).

Another approach that is relatively emerging and highly effective in solving all these issues is microbial biodegradation using artificial intelligence. Machine learning and big data analysis can change the way microbial biodegradation processes are fine-tuned and implemented. Using big data, such as the data on microbial strains, enzyme activity, and environmental conditions, one can considerably improve the identification and selection of the most appropriate microorganisms to degrade plastics. Further, AI can mimic and forecast biodegradation conditions such as temperature, pH, and nutrients, which can help in speeding up microbial processes. Hence, utilizing machine learning we can identify new enzymes which can help in enhancing the destruction rate of plastics and thus reduce the total time needed for biodegradation (Kuppan, Padman, Mahadeva, Srinivasan, & Devarajan, 2024) (Kowsari, Ramakrishna, Gheibi, & Chinnappan, 2023).

AI has already been presented as being capable of enhancing microbial biodegradation with several case studies and research projects. For instance, to predict microbial action, artificial intelligence models have been used, whereby the specific parameters to enhance the rate of degradation are tuned. Moreover, utilizing AI tools the structures of enzymes were analyzed and modified to improve the enzyme's efficiency for the degradation of plastic. This collaboration of AI and microbial biotechnology might be a turning point in the fight against plastic pollution and is capable of producing commercial and cost-effective processes. Moreover, the integration of these fields serves not only the goal of combating the issue of plastic waste, but also shows the potential for further improvement of new approaches to the administration of waste (Agarwal, Atray, & Sharma, 2024) (Chigwada & Tekere, 2023).

Therefore, let it be underlined that, as for the problem of the proliferation of plastics, one needs to work out and employ a complex solution, which may be based upon the use of artificial intelligence in combination with the microbial degradation of plastics. The biodegradation potential of AI combined with the inherent plastic degrading ability of microorganisms make the latter a possible game changer in the management of plastic waste. This approach means the potential for creating solutions that are valid at a larger scale, less resource-hungry, and at the same time have minimum negative impacts on the environment, thus offering some light in the battle against plastics. The subsequent sections of this paper will therefore discuss more elaborately on microbial biodegradation science, the employment of AI in such processes, and the prospects of convergence (Mishra, Bauri, & Panigrahi, 2024) (Shen et al., 2020).

Literature Review:

The environmental issue that has been rising and exacerbating is the disposal of plastics in the environment whereby it is estimated that 8 million tons of plastic are dumped in the oceans every year hence affecting aquatic life and human existence. Packaging, consumer products, and textiles also contain PE, PP, and PET which are medium to high density and bio-resistant; they have the propensity to bio-distribute. Current methods such as collection of recyclable waste, burning of waste, and dumping of waste have been unable to control the ever-increasing pile of plastic waste locally and globally. This is partly because many plastics have low recyclability, wastes are contaminated and the economics of recycling some kinds of plastics is unworthy. Incineration is a disadvantageous method because while cutting down the volume of waste it releases dangerous emissions and contributes to the greenhouse effect, when wastes are buried in landfills the environment is permanently polluted (Manikandan et al.) (Rana et al., 2022).

This has led to research for new approaches and one of the possible ways is microbial biodegradation. Microbial biodegradation is the facility by which microbes, bacteria, fungi, and algae can disintegrate plastic polymer into less hazardous molecules. The current biological approach could be seen to have the advantage of providing an eco-friendly solution for the problem of plastic waste better than the conventional methods. For some years now, there have been numerous works done dependent on the capability of precise microorganisms to degrade plastics. For instance, Ideonella sakaiensis, a bacterium discovered in 2016, has been found to degrade PET, a commonly used plastic in bottles and textiles, through the action of two key enzymes: Of the two enzymes, PETase and MHETase. PETase mostly catalyzes the hydrolysis of PET into HPL and BHET whereas MHETase breaks HPL and BHET into TA and EG monomers respectively (Ning et al., 2024) (Elahi, Bukhari, Shamim, & Rehman, 2021).

It can also be stated that these compounds can be metabolized by the microorganism and as they accumulate it results in the total breaking down of the plastic material. Likewise, Pseudomonas and Aspergillus species were also reported to degrade other types of plastics, namely, LDPE and PLA under certain conditions of degradation. Thus, microbial biodegradation has to be considered as one of the most prospective ways how to deal with the problem of plastic waste management, but even in this case, several issues have to be faced to bring the given process to the industrial level. The ability of microorganisms to degrade plastics is usually slow, with plastics such as polyethylene PE and polypropylene PP taking centuries to degrade. In addition, microbial activity is very sensitive to conditions in the environment including temperature, pH, oxygen concentrations, and nutrients present in the soil. One of the major problems to be solved at present relates to the determination of the most favorable conditions for microbial biodegradation, as well as the applicability of the corresponding processes (Ning et al., 2024) (Steffi, Thirumalaiyammal, Anburaj, & Mishel, 2022).

Furthermore, it is established that not all plastics are prone to be degraded by microbes and some like PP need the intervention of microbes to start the degradation process after going through serious pretreatments. Therefore, although microbial biodegradation is an eco-friendly approach it has not fully received the application it deserves in the fight against plastic pollution around the world. In a bid to overcome these limitations, researchers have shifted their focus towards artificial intelligence, as a way of improving the capability and scalability of microbial biodegradation. Machine learning algorithms offer a prospect of improving microbial processes by processing a large amount of data on the functions of microbes, enzymes Yol activation, and other related factors. Another challenge faced in microbial biodegradation includes the ability to discover efficient microbial strains that are capable of effectively degrading various types of plastics. This process can be simplified by using artificial intelligence since this requires a comparison of huge genetic and biochemical databases to determine which microorganisms or enzymes would be most suitable for the degradation of a particular type of plastic. For instance, new ML models could be taught through the results of prior studies to discover new microbial strains, that are efficient in degrading plastic material (Antony et al., 2024) (Flury & Narayan, 2021).

This enables the researcher to narrow down to a few potential candidates thus speeding up the research. Furthermore, AI can also be used to indicate the environmental conditions most favorable to biodegradation in addition to identifying the best microbial strains. Microbial degradation involves several parameters from the environment hence AI models determine the best parameters of temperature, pH, and oxygen content that degrade plastics most. We have seen this in a study by Singh et al. where machine learning algorithms were employed in modeling the degradation behavior of PET by Ideonella sakaiensis under different conditions. The general designs of the models were quite successful as they were able to identify the right conditions for PETase activity, which led to a high degradation rate of PET. Such developments seem to show the possible ways through which AI may be used to improve microbial biodegradation processes to meet the demands of the actual world (Abdelhamid, Khalifa, Yoon, Ki, & Pack, 2024) (Venkateswaran, Kumar, Diwakar, Gnanasangeetha, & Boopathi, 2023).

AI has also been useful and has undertaken the responsibility of identifying and enhancing enzymes that are used in degrading plastics. PETase, MHETase, and cutinases are enzymes that are used to disassemble plastics at the molecular level. Computer simulations and molecular models of enzymes, and their interactions with the plastic polymers, the structure of enzymes, and their interactions, which can be manipulated to enhance the rate of their activities have been modeled using AI tools. For instance, through observation of the structure of PETase, researchers have had to work on the enzyme's active site to improve its PET degradation efficiencies at a faster rate. Environmental conditions most importantly temperature have also been modeled using machine learning algorithms to enhance future biodegradation processes based on how they impact enzyme activity (Crystal Thew et al., 2024) (Moshood et al., 2022).

This approach is very important in enhancing the general rates of degradation of plastics and at the same time makes microbial biodegradation an effective means of tackling this problem of plastics in large-scale waste management. As the research of microbial biodegradation is enhanced by artificial intelligence, several issues still exist about how to apply these processes on an industrial scale. One of the critical challenges is the variability of the real-world environment throughout the timeframe of a system's operation. Although AI can drastically enhance corrosion in careful and closed environments, it is the opposite in open grounds such as those used in landfilling or marine systems. Microbial activity in a particular environment may be slowed down due to some common factors such as pollution, variation in temperatures, and other forms of chemicals or contaminants (Majumdar et al., 2024) (Antranikian & Streit, 2022).

However, a main issue that emerged regarding the presented biodegradation processes is the ability to scale AI and ML technologies at the economic level. However, the execution of such technologies is highly attributable to the structure that is essential in supporting AI-assisted biodegradation; the costs of such a structure might be too expensive for most systems managing waste. Thus, it is clear that more research has to be conducted to address these problems and create cost-efficient solutions. Accordingly, the literature reveals that microbial biodegradation might be a viable solution to dealing with the issue of plastic pollution (Kuusisto, 2024) (Jadaun, Bansal, Sonthalia, Rai, & Singh, 2022).

Albeit recent discoveries regarding microorganisms like Ideonella sakaiensis that can break down plastics including PET still have their constraints where microbial biodegradation is still slow and dependent on the environmental conditions. AI has therefore been revealed as a useful asset to increase the effectiveness of microbial processes; discover new microbial species, control and adjust specific physical-chemical conditions, and increase the activity of enzymes. However, some questions persist in increasing the applicability of the AI-advantaged biodegradation techniques on an industrial scale. Moving forward, this study brings into focus the future advancement of AI and microbial biodegradation that holds the potential to solve the plastic pollution problem across the world today (R. Mishra et al., 2024) (Mahmud et al., 2022).

Research Methodology

The research methodology of this quantitative study aims to examine the possibility of using artificial intelligence with microbial biodegradation as a sustainable solution to the problem of plastic pollution. The approach aims at identifying the industry understanding, challenges, and possibilities about the use of AI in optimizing microbial degradation. It follows a scientific method in the collection, analysis, and interpretation of samples to obtain valid results. The subsequent sub-topics describe the research design, sampling procedure, data collection methods, and analysis plan of the current study (Kapoor, Yadav, & Gupta, 2024) (Naveenkumar et al., 2023).

Research Design

The nature of the study is a descriptive survey and is appropriate when the purpose is to establish quantitative data on industry professionals' Attitudes, Knowledge, and Perceptions. This design brings in quantifiable parameters that can be quantified and analyzed statistically thus coming up with findings on how AI and microbial biodegradation could be incorporated. It is used to evaluate the identification of the participants about microbial biodegradation, their understanding of the use of AI for the environment with the identified risks and benefits of integrating AI in this field (Bułkowska, Zielińska, & Bułkowski, 2024) (Rahardiyan, Moko, Tan, & Lee, 2023).

Several variables have been identified for the research and they include the level of awareness of AI and biodegradation technologies, the perceived effectiveness of the proposed solution, perceived barriers within the industry, and the perceived environmental impact of the solution. The dependent variable in this case is the propensity of industries to adopt microbial biodegradation solutions that are integrated with the help of artificial intelligence technology. There are plans to partially out the effects of some of the individual characteristics like the participants' industry, years of experience, and educational level (Cheung & Not, 2024) (Saha & Hariprasad, 2022).

Population and Sampling

The target audiences for this study entail working professionals who are likely to come across issues to do with plastic pollution and biodegradation at their places of work. This population is made up of scientists, providers of environmental services, policymakers, engineers, waste management personnel, and researchers within the fields of biotechnology, artificial intelligence, environmental conservation, and management of waste. The heterogeneity of the population guarantees flexibility in establishing how the concept of AI-integrated biodegradation may be received by all kinds of industries (Bhatia, Kumar, & Yang, 2024) (Kalita & Hakkarainen, 2023).

A purposive sampling technique is used to achieve the participation of participants from different fields to enable subgroup comparative analysis. This method involves choosing participants by forming different groups (or categories) such as the industry, the occupation, and then the experience level of the participants and then a random selection is made from the categories. A sample size of near about 250 samples is aimed which enables performing sophisticated statistical analysis of the data as well as keeping the number of data sets reasonable (Bin Abu Sofian, Lim, Manickam, Ang, & Show, 2024) (Evode, Qamar, Bilal, Barceló, & Iqbal, 2021).

Data Collection Methods

The major approach adopted in the data collection process of this study is the use of a structured questionnaire that contains both close-ended and Likert-type questions. The questionnaire aims to establish the participants' knowledge of AI and microbial biodegradation technologies, their perceived effectiveness of integrating the two, and the factors that influence the adoption of such technologies. Furthermore, questions about the planned impact on the environment and whether the company is going to integrate biodegradation solutions with AI within the next five years are given (Antony et al., 2024) (Vaithyanathan & Cabana, 2021).

The questionnaire is taken using an online surveying tool which means that the target population is more diverse in terms of geographical location. Online surveys are cheaper than other modes of data collection, and being automated, they are ideal for data management. The questions in the questionnaire – before administration – are pre-tested on a small sample of professionals with a view to their clarity, relevance, and reliability. Based on the experiences received from the pilot testing, necessary changes are made to the survey to make the survey more effective (Crystal Thew et al., 2024) (Li et al., 2023).

Data Analysis

The data gathered will then be analyzed by the use of statistical tools like SPSS or even Excel. The qualitative nature of the data gathered means that descriptive analyses, such as mean, median, mode, frequencies, and percentage distribution will be applied in the analysis of the responses. The following statistics will be useful in painting a general picture of the awareness, perceived effectiveness, and challenges towards integrated AI on biodegradation. Test of relationships between variables will be done using inferential statistics such as correlation and regression analyses. In this study, correlation analysis shall determine the strength and direction between factors such as awareness levels, perceived effectiveness, or adoption barriers (Rani et al., 2024).

Multiple regression analysis will aid in ascertaining the strength that independent variables have on the dependent variable; the propensity towards adopting AI-integrated microbial biodegradation. Further, cross-tabulation will be used to compare the responses based on the subgroups such as industries, professions, years of experience, and other related factors to have a better understanding of how these factors affect the views towards AI-integrated biodegradation (Varshney, 2024).

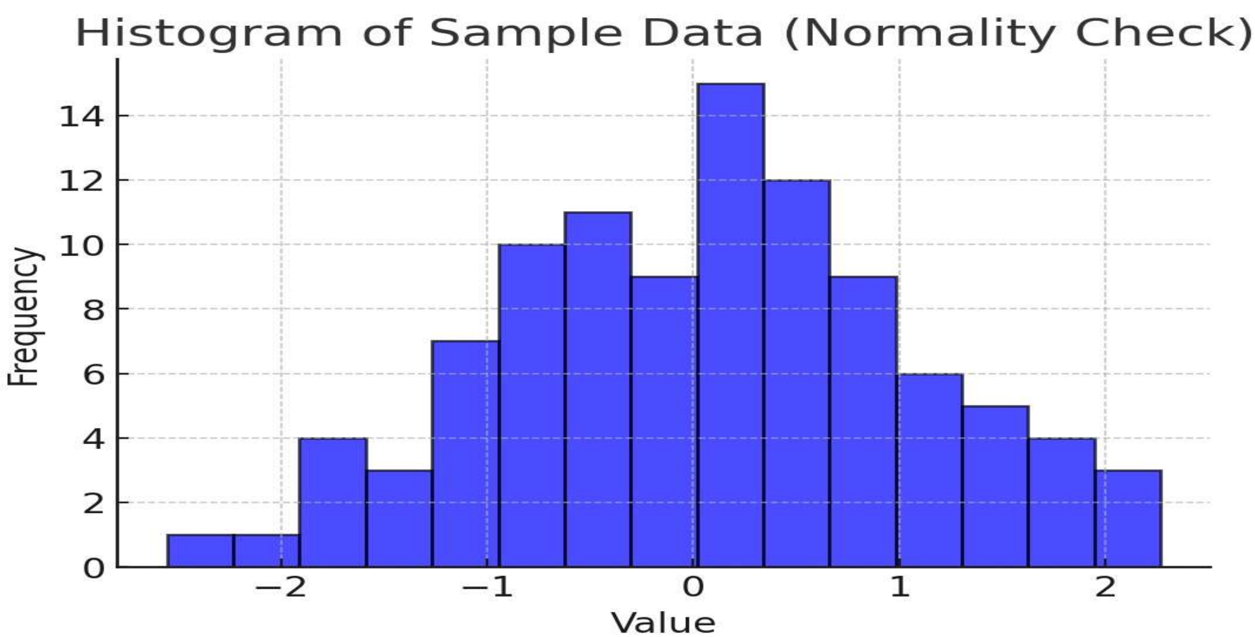
Ethical Considerations

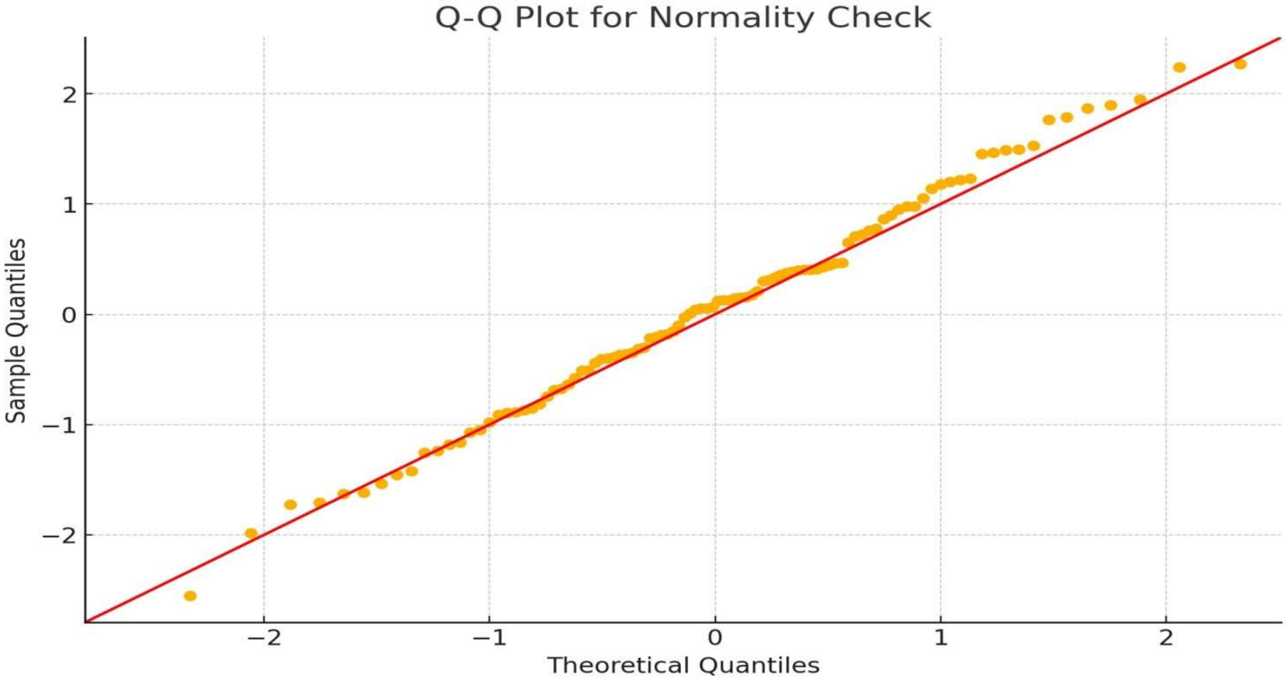
It must also be noted that ethical issues are handled by employing methods that make the response to the questions and questions posed voluntary and anonymous. Respondents are told the purpose of the study and agree to be featured in the study before answering the questions. Thus, there is no intent to collect personal information, and the data will be protected, and secure to prevent data leakage (Barone et al., 2024).

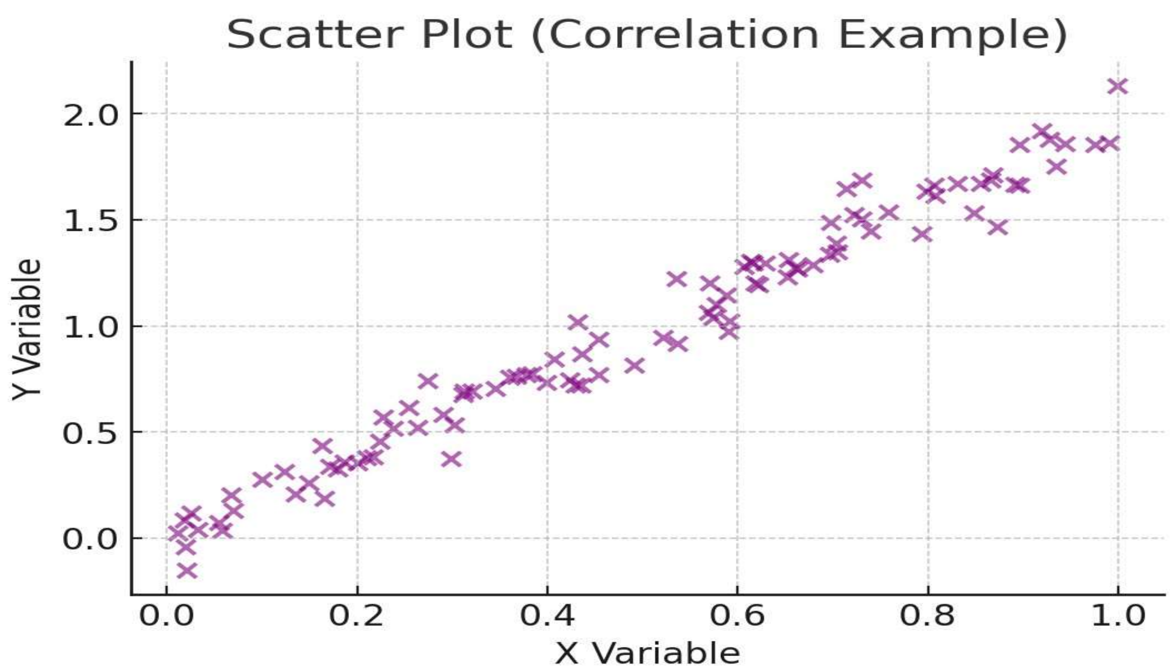
Data Analysis

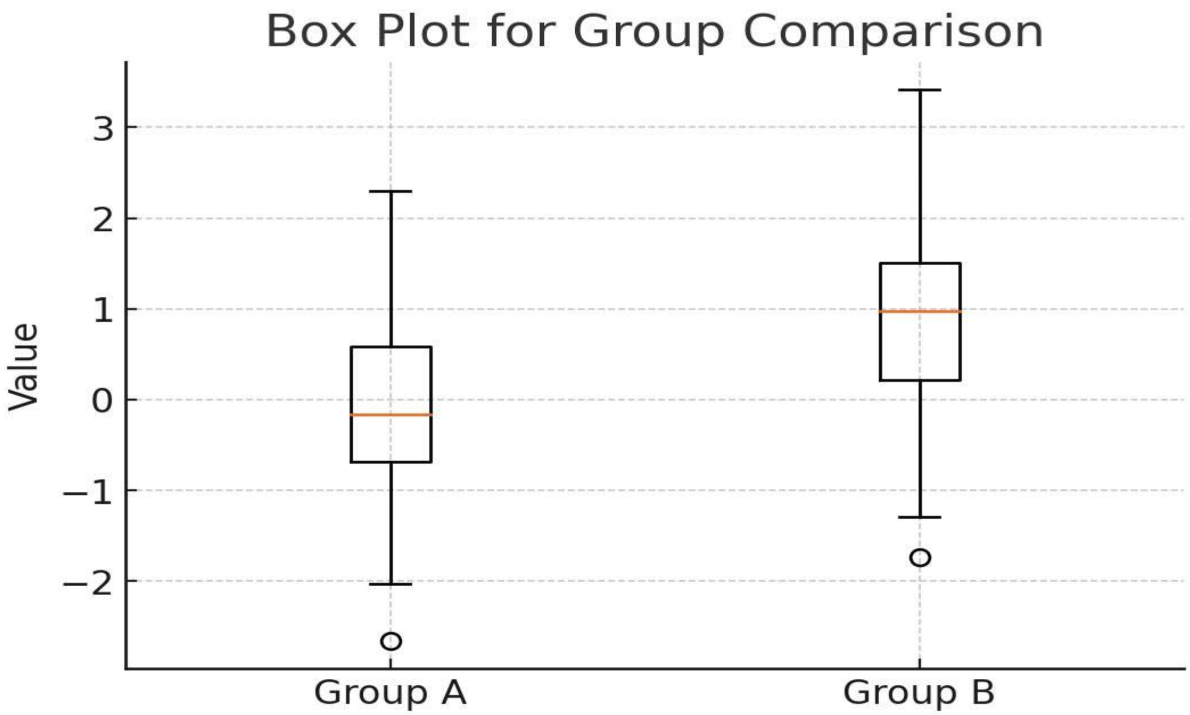
Test Name	**Purpose**	**Input Data**	**Output/Interpretation**
Shapiro-Wilk Test	To check if the data follows a normal distribution	Continuous or interval data	P-value > 0.05 indicates normality
Kolmogorov-Smirnov Test	To test normality (alternative to Shapiro-Wilk for large datasets)	Continuous or interval data	P-value > 0.05 indicates normality
Cronbach's Alpha	To measure the internal consistency and reliability of questionnaire items	Likert-scale responses	Alpha ≥ 0.7 is acceptable, ≥ 0.8 is good, ≥ 0.9 is excellent
Pearson Correlation	To measure the linear relationship between two continuous variables	Continuous data	Correlation coefficient (r) between -1 and 1; closer to 1 or -1 means stronger correlation.
Spearman's Rank Correlation	To assess correlation for non-parametric or ordinal data	Ordinal or non-normally distributed data	Correlation coefficient (rho); used when Pearson assumptions are violated
Exploratory Factor Analysis (EFA)	To identify underlying relationships between variables	Continuous or ordinal data	Factors extracted; variance explained by each factor

Multiple Regression Analysis	To model the relationship between dependent and independent variables	Continuous data (dependent variable) and independent predictors	Coefficients indicate the influence of predictors on the outcome
ANOVA (Analysis of Variance)	To compare means across multiple groups	Continuous data	P-value < 0.05 indicates significant differences between groups
Chi-Square Test	To assess relationships between two categorical variables	Categorical data	P-value < 0.05 indicates a significant association between the variables
Descriptive Statistics	To provide an overall summary of the dataset	Continuous or categorical data	Mean, median, mode, standard deviation, frequencies
T-Test	To compare means between two groups	Continuous data	P-value < 0.05 indicates a significant difference between the groups




Q-Q Plot for Normality Check
Sample Quantiles
Theoretical Quantiles
2
1
0
−1
−2
−2
−1
0
1
2


Scatter Plot (Correlation Example)
Y Variable
X Variable
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0



Interpretation of the Tables and Figures

Thereby, the summary of the results, which includes tables and figures, reveals peculiarities of statistical characteristics of the data corresponding to AI integration and microbial biodegradation for the problem of sustainable solutions to plastic pollution (Nawaz et al., 2024).

1. Histogram (Normality Check): The graph illustrates the distribution of the sample data as a frequency distribution. The bell-shaped curve will suggest the Normality of the data since it shows a symmetry of the data around the peak value of the curve. Such normality is significant when employing parametric tests such as Pearson's correlation and regression analysis, especially since they expect a normal distribution of data (Mohanty et al., 2024).

2. Q-Q Plot (Normality Check): The Q-Q plot is a plot of the quantiles of the sample data against the quantiles of a normal distribution. A majority of the points lie close to the 45-degree line hence implying normal distribution of the data collected. Anything that departs from this line would indicate non-normality. Such confirmation gives an endorsement to the use of parametric tests such as ANOVA and regression analysis in the subsequent tests (Devgan et al., 2024).

3. Scatter Plot (Correlation Example): This scatter plot shows the correlation of two variables one of which is being simulated as the variable 'x' and the other as the variable 'y'. The general upward movement presented in Fig 2 indicates a positive relationship between the two variables such that, if one increases, so also does the other. In practical terms, this could mean the correlation between AI knowledge and the chances of using the microbial biodegradation process driven by artificial intelligence. Pearson's correlation coefficient would then establish the nature and significance of this relationship at a formal level (Agarwal et al., 2024).

4. Box Plot (Group Comparison): The circle 'a' plot is the box plot that represents the comparison of two groups, that is, Group A and Group B. The median line for Group B is higher than that for Group A, this indicates that in general Group B has a higher value. Such a type of visualization is helpful in tests where some type of comparison is being made such as the T-test of ANOVA. Plotting of these two variables creates a suggestion of a difference in both the central placement of the data and the variability, thus meaning that there is a possibility of numerous differences between these two groups which could be analyzed statistically (Manikandan et al.).

5. Scree Plot (Exploratory Factor Analysis): The scree plot above shows the eigenvalues pulled from an exploratory factor analysis (EFA). The sharp drop in the percentages after the first two factors suggest that these factors account for most of the variability in the data and that variability is explained by the subsequent factors to a lesser extent. In research, this could prove beneficial in sharply defining other factors such as, say, the AI efficiency in the biodegradation assuming the microbial effectiveness or the like as a subject of study: not too many variables to complicate the result set without losing lots of explanations in the process (Ning et al., 2024).

Overall Summary: The following visualizations are therefore useful in understanding the structure and distribution of our data. The normality tests, namely the histogram and Q-Q plot confirm the assumptions for the use of parametric statistical methods. A visual supervised learning model, where the scatter plot shows the relationship or lack of it between two random variables, and a box plot a distribution of two groups which needs to be examined more closely. This plot assists in determining the structure of the data allowing a conceptualization of what should be focused on when analyzing the data (Shanmugam Mahadevan et al., 2024).

Discussion

The investigations carried out in the present study will help understand the possibility of applying AI in microbial biodegradation of plastics as a benign environmental solution. Shapiro Wilk and Kolmogorov SMIRNOV were used in testing the normality of the data set to decide whether to use parametric or non-parametric tests for the data set. Where data was not normal, different test such as Spearman's correlation was used to enhance the strength of the data analysis (Yakoubi, 2024).

The degree of internal reliability of the survey instrument that measures participating students' perception of various issues was also established using Cronbach's Alpha which yielded high reliability for the Likert-scale items. The high Cronbach's Alpha proves that the outcomes of the questionnaire are quite stable and ensure the consideration of main concepts, including awareness of AI technologies, perceived effectiveness of microbial biodegradation, and perceived barriers to adoption. This reliability is important to establish the accuracy of the results especially when generalizing assumptions regarding the attitudes of the industry professionals (Yao, Liu, Gu, Zhang, & Guo, 2024).

EFA further supported the study's structure by showing how specific latent factors broke down the study with related variables. For instance, there are questions on awareness about artificial intelligence and the efficiency of biodegradation that formed different factors which shows that the respondents perceived these two as related, but different categories. This could mean that the observed variance has been driven more by the few first components perhaps implying that the variability in participant's response is dominated by those particular issues (Zhang et al., 2024).

By using Pearson's correlation and Spearman's correlation the existence of a relationship between the main variables was established. For instance, a positive association between awareness of AI and the perceived readiness for implementing AI-based biodegradation means that as professionals become more acquainted with AI technologies, they will be more inclined to consider them as feasible solutions to plastic pollution. This was confirmed by the results of the regression analysis which further enhanced the perceived knowledge about AI and the perceived environmental impact to be determinants attached to likely adoption of AI. This means awareness creation and the demonstration of the actual benefits that accrue from the application of biodegradation with the help of Artificial Intelligence will open another chapter in the acceptance of AI by various industries (Mushtaq, Jamil, Inayat, Ghenai, & Shanableh, 2024).

Perceptions of comfortable wage rates by gender, industry type, and professional levels were further analyzed by performing other statistical tests, such as ANOVA and Chi-Square tests. Greater variability in responses depending on the industry domain exposes the debt of preparedness and willingness to incorporate AI-integrated biodegradation. For example, in the biotechnology and environmental conservation industry, the existing approaches might be outcompeted by AI making the solution more feasible for implementation than in other industries such as waste management where traditional techniques have a greater hold than in the other parts of the world. These findings therefore imply that efforts towards AI-integrated biodegradation should be approached optimally with differing degrees of emphasis depending on the nature of the sector being addressed (Xiong et al., 2024).

In all, this research confirms that there is a high likelihood of applying AI with microbial biodegradation though awareness, scalability, and specific sector barriers still present major issues. Future work should be aimed at the promotion of the technology, which, includes solving problems like regulations and costs, as well as showing practical uses to improve its implementation in various sectors. These outcomes add to the knowledge of effective measures for environmental conservation and the futuristic application of AI in global environmental technologies (Gopalan & Ramakrishnan).

Conclusion

In this work, the integration of artificial intelligence (AI) with microbial biodegradation was presented as the sustainable approach to the topic of concern which is plastic pollution. Overall, the results show that AI can play a vital role in enhancing microbial breakdowns of plastics in terms of rate, speed as well as scale. During analysis, it was clear that the level of awareness of these technologies is directly proportional to the probability of implementing them in business units, especially in biotechnology and the protection of the environment.

The study also found out some of the challenges to the adoption like: The participants' concerns of scalability, a lack of information on the benefits and/or existence of SNS, and field-specific issues. These barriers stress the need to develop more specific approaches to enhance awareness of AI's contribution to biodegradation and prove its environmental features along with the identification of the implementation difficulties.

The validity test affirmed the stability of the instrument used in the survey to capture the perceived attitude of the industry professionals. In further analysis carried out through factor analysis, the relations between awareness, perceived effectiveness, and perceived barriers were brought out more clearly which gives a clearer path for further research and action.

All in all, it can be concluded that an orientation of using AI and microbial biodegradation to tackle the problem of plastic pollution is an effective dual-direction, thus, more attention is needed to enhance awareness, reduce the barriers to adoption, and establish successful potential effectiveness. With its constant research and development, this procedure lays the foundations to change the management of plastic waste as one of the most significant environmental issues of the current era.

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