# Perception of Predictive Analysis Impact on Maintenance Practices and Decision-Making in the Facility Management Program at BUas

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**Abstract**

It's a well-known fact that the integration of Artificial Intelligence (AI) into our daily lives raises concerns in the people around the world. Like any other thing, AI has its advantages and disadvantages. Breda University of Applied Sciences recognizes the huge influence of AI and data science on various fields and aims to integrate these technologies into the curriculum across all domains. The university acknowledges that AI will impact every profession, and therefore, they've look for the assistance of students of Data Science and Artificial Intelligence to prepare a policy paper offering guidance on implementing AI in these domains.

Our group's specific focus is on the Facility Management program. My individual project goes deep into the influence of predictive maintenance on decision-making within BUas's Facility Management program. We employed a mixed-method research approach, which consists of qualitative and quantitative methods such as interviews and surveys. The objective was to find out the perspectives of both students and staff involved in facility management regarding AI. The outcomes of our research reveal a shared awareness among students and staff about the changes AI will bring.

*Keywords:* Artificial intelligence, facility management, predictive maintenance

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## Introduction

Artificial intelligence (AI) is a subfield of computer science dedicated to create systems capable of performing tasks that typically require human intelligence, such as problem-solving, learning, reasoning, perception, and language understanding. Real-life examples of AI applications include Siri for natural language processing, Duolingo for adaptive learning, Google's AI-enhanced search algorithms, and Spotify's AI-driven recommendations.

AI has impact on many domains, including facility management, which focuses on creating efficient, safe, and pleasant work and living environments. AI in facility management can improve maintenance, space utilization, and energy efficiency, introducing automation, sustainability, and efficiency. For example, AI can optimize energy consumption in buildings and improve security by analyzing surveillance data to identify potential threats.

This scientific report specifically examines predictive maintenance in facility management. Predictive maintenance (PdM) utilizes technologies like data mining, and AI to enhance maintenance practices, aiming to reduce costs, maximize reliability, and optimize machinery health. This research takes a mixed-method approach, combining qualitative interviews with quantitative surveys among facility management students and staff at BUas. The objective is to help the university integrate AI, particularly in predictive maintenance, within its facility program.

### Research Questions

This sections present all the research questions, which were made for making this research possible. There are 1 qualitative and 3 quantitative questions. Combining these 4, it can be done more in depth understanding. The qualitative questions, which is also the central one, is the following:

*How do maintenance professionals perceive the impact of predictive analysis on their maintenance practices and decision-making?*

To provide an answer to this research question, we have come up with the following quantitative subquestions:

1. What is the potential impact of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas on academic performance and skill development of students?
2. What is the measurable effect of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas on the skill development of students?
3. What is the relationship between students' exposure to AI-based predictive maintenance techniques in their coursework and their ability to effectively apply these techniques in practical facility management scenarios?

**Hypothesises**

To be able to conduct the research and answer to quantitative research questions by data analysis, hypothesises were formulated for the second and third questions. They are ordered respectively as followed:

- $H_0$ The mean impact rating of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas is equal to a specific value.
- $H_0$ There is no significant relationship between students' exposure to AI-based predictive maintenance techniques in their coursework and their ability to effectively apply these techniques in practical facility management scenarios.

## Literature Study

In the realm of facility management and maintenance, in the paper Shen et al., 2012 offered a promising approach. This source emphasizes the integration of data, information, and knowledge throughout the entire lifecycle of a facility. It employs agent-based web services to facilitate this integration and provide decision support. Notably, the focus is on optimizing facility operations, and the proposed approach has been validated through case studies with prototype implementations.

In the survey Ran et al., 2019, we are shifting our attention to the field of predictive maintenance (PdM). This paper dives into the limitations of traditional maintenance methods and underscores the emergence of PdM driven by IoT, data mining, and AI technologies. It explores various PdM system architectures, outlines maintenance objectives (including cost minimization, reliability maximization, and multi-objective optimization), and categorizes different PdM approaches. These encompass knowledge-based, traditional Machine Learning (ML)-based, and Deep Learning-based techniques. The paper concludes by highlighting key research directions in the evolving landscape of PdM.

In the context of Industry 4.0, in the paper Sajid et al., 2021 the authors underscore the critical role of data science. It emphasizes the importance of regular maintenance in the increasingly complex machinery of modern industrial settings. The paper supports for the involvement of data analysis experts to diminish breakdowns, address quality issues, reduce costs, and enhance manufacturing efficiency. It further highlights the integration of data science with Industry 4.0 and outlines the pivotal processes employed by data scientists in the domain of predictive maintenance.

Finally, in article Çınar et al., 2020 the focus is set on the main role of predictive maintenance (PdM) within the context of Industry 4.0. This research highlights the extensive adoption of PdM, assisted by smart systems and machine learning (ML) techniques. PdM is recognized as an essential part for smart manufacturing, offering ways to monitor and optimize the health of industrial equipment. The paper categorizes and reviews recent ML advancements in this domain, based on algorithms, machinery types, data gathering methods, and data types. These categorizations provide a solid foundation for further exploration and research within the growing field of PdM in Industry 4.0.

# Method

The methods section of this research outlines the approach and procedures used to investigate the integration of Artificial Intelligence (AI) within the Facility Management program at Breda University of Applied Sciences (BUas). A mixed-methods research design is employed, combining both qualitative and quantitative methods.

## Design

Mixed-method approach was used to comprehensively understand the research topic, combining qualitative and quantitative data sources for a better perspective. Qualitative data was gathered through semi-structured interviews with volunteers from the facility management program, focusing on integrating artificial intelligence in their program. Quantitative data was collected via a Qualtrics survey distributed to all domains, featuring closed-ended and Likert scale questions.

Interview data went through thematic analysis, involving systematic coding and categorization by each group member. This approach yielded diverse concepts and perceptions regarding predictive maintenance. Quantitative survey data was analyzed using R, including descriptive statistics and visualizations for data overview. Inferential statistical methods, such as t-tests, correlation analyses, and linear regression, were used to reveal connections between the variables of interest.

## Materials

For data collection and analysis, digital tools and software were used. We recorded interviews with the participants using Microsoft Teams, so it can be also extracted the transcript of the interview (with the agreement of each participant. To collect quantitative data, we created and distributed surveys through Qualtrics. Before participating in the survey and the interviews, people were sent informational consent form. The collected data was then analyzed using the R programming language, a versatile tool that helped us understand the information we had gathered. These tools and materials made it possible to study how students and teachers from facility management view the impact of predictive analysis on the study program.

## Participants

The research's goal was to collect data from all facility management students, but this proved to be impossible. The team faced challenges in finding willing interview participants, and only a small part of the program's students, teachers and staff responded to the survey (total of 50 students, teachers, and staff). However, compared to the participants from the other courses, it can be noticed that the number 50 is not actually low at all. In this analysis, a sample was taken from the initial group of 50 individuals, all from the facility management program, and another sample consisted of 10 individuals who had responded to my questions, which are related to predictive maintenance. The reason of that is that the survey, which was made from the group was so long that it was given the option to participants to choose between each component in facility management such as space optimization, safety, energy efficiency and predictive maintenance as 10 choose to respond the questions related to the latter.

## Procedure

For the purpose of the project, both qualitative and quantitative data were collected. Data collection began in the third week of the project (20.09.2023) and continued until its conclusion on 03.11.2023.

In terms of quantitative data, a Qualtrics survey was created, comprising general questions and specific questions for each domain. In our project, we included general questions related to facility management and divided the survey into four sections, allowing participants to choose their preferred component: energy efficiency, space optimization, safety, or predictive maintenance. The questions included both closed-ended and open-ended questions. To distribute the questionnaire, QR codes were placed around the university campus, which directed participants to the survey link.

Regarding qualitative data, semi-structured interviews were conducted. Similar to the survey, the interview structure was divided into several sections: one general section and four sections corresponding to the components mentioned earlier. Participants were reached through various means, including coordination with teaching staff and assistance from the facility management representative.

After collecting the data from the survey, it was extracted from Qualtrics in the form of two CSV files containing both numerical and text data. These files were prepared for cleaning and analysis. The data was filtered and subsetted to include only the information relevant to the project's focus on facility management and predictive maintenance. Furthermore, exploratory data analysis and hypothesis testing were performed using the R programming language.

**Data Analysis**

In this section it will be described the techniques, which were used for analysing the collected data. Firstly, it was checked the number of people from facility, who have participated in the research, because that's the population, in which we are focused. Secondly, the structure of data was explored along with detecting missing data. It can be noticed that there are entire rows with missing values, so it can assumed that the survey was opened, but not finished. Furthermore, there are cases, where the participants did not finish the survey, so the questionnaire probably was too long. Afterwards, when the data was sampled to this from the participants from facility program, it can be noticed that for the some of the questions there is missing data as well. This is caused by the fact that the participants could not answer to all the questions, because there was an option to choose between a component, which they prefer to answer the questions the most. Moreover, exploratory data analysis was performed as mostly bar charts were used, so it can be made better comparison between the results. The data from the demographic, facility and predictive maintenance questions were plotted. Finally, inferential methods were used as one sample t-test and linear regression were used. For the qualitative part, semi-structured interviews were conducted, so it can be get a better perception and more depth of the data from the survey.

### *Instrument*

An instrument, which was used for gathering data, is the survey as it was used Qualtrics. In this section, we evaluate the reliability and validity of the survey to ensure that the gathered data is not only accurate but also meaningful.

**Reliability.** In this paragraph, the reliability is about how consistent and stable is the survey. Two things will be observed in this paragraph - inter-rater and test-rater reliability.

***Inter-rater reliability.*** The participants have the option to answer questions based on the Likert scale as this allowed them to express responses using a range from 1 to 5. While the Likert scale typically uses responses ranging from "strongly disagree" to "strongly agree," for the questions related to predictive maintenance, a different type of scales were used, including options such as 1 (Not at all), 2 (To a minimal extent), 3 (Somewhat), 4 (To a significant extent), and 5 (Fully integrated).

***Test-retest reliability.*** To evaluate the survey's consistency over time, we conducted two separate surveys. The results from these surveys were compared to those from the primary research survey. The consistency in responses in both surveys demonstrated the reliability.

**Validity.** The parent survey was made by the mentors of the program Data Science and Artificial Intelligence and as each group put their respective questions. The questionnaire was tested by the students before it was sent active.

***Face validity.*** The questionnaire was tested by students and staff before it was made active. Some changes were made such as the facility management part was made shorter, because it seemed to be to long. It was made in a way that the students can choose to what component of facility management to answer. Afterwards, the survey was assessed well and published.

***Construct validity.*** The survey is trying to find out what can be impact of predictive maintenance on decision-making on the facility management program at BUas. The questions are relevant as the students were asked whether Artificial intelligence will have impact on their skills development and on applying the gained knowledge about predictive maintenance in the industry.

## Results

In this section, it is present a comprehensive view of our research findings. It is included both quantitative data, which offers numerical insights and statistical analyses, and qualitative data, which provides in-depth narratives and thematic explorations. Together, these results offer a better understanding of the research topic, bridging the gap between quantitative measurement and qualitative interpretation.

### Quantitative findings

As it was mentioned previously in the report, for the quantitative part of the research it was made survey, which was spread around the students. There were in total 50 respondents from facility management program as it can be seen in Figure 1.

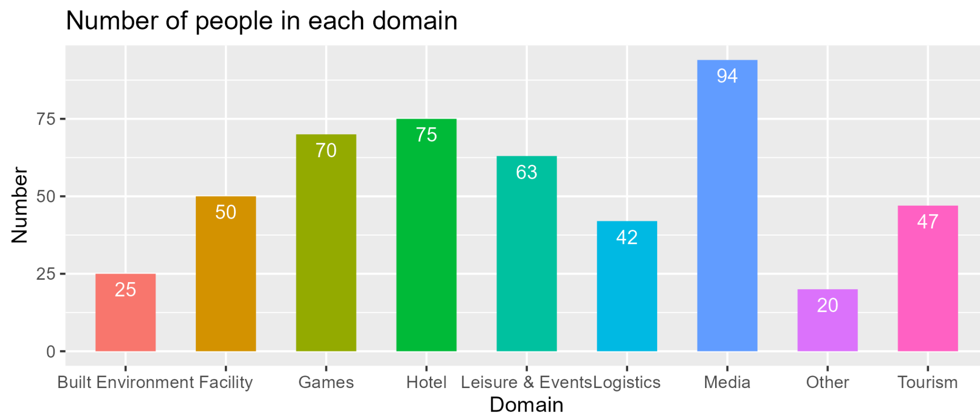


**Figure 1**

*Number of people in each domain.*

Also, there was demographic data collected as it can be noticed from Figure 2, the most of the respondents are female from 18 to 24 years old and then the male as the same group age is with most respondents. By contrast, there is one respondent of each ">65" and "35-44" as none of this age group are female. Furthermore, one of the participants choose the option "prefer not to say" as the same person decided to not specify their age.

Furthermore, the participants of the survey were asked what is their AI knowledge and how familiar they are with machine learning and deep learning. As it can be seen in figure 3, most of the respondents do not consider themselves to have good understanding of what is AI as the most common response from the educators is "Somewhat bad" and from the students is "Neither good nor bad".

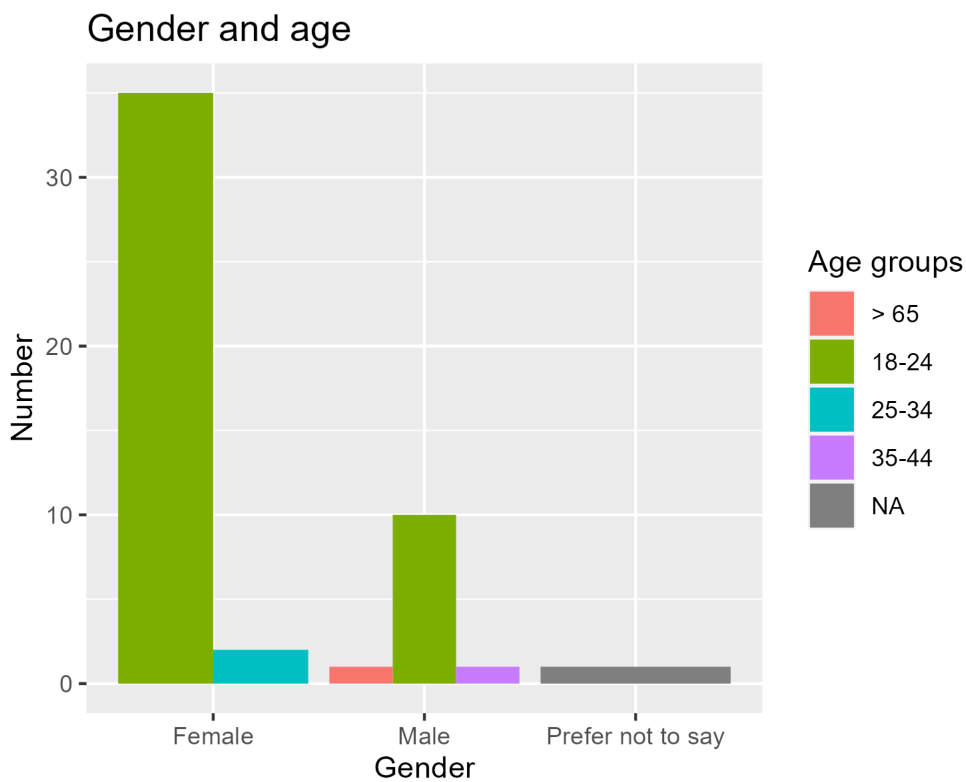


**Figure 2**

*Genger and age.*

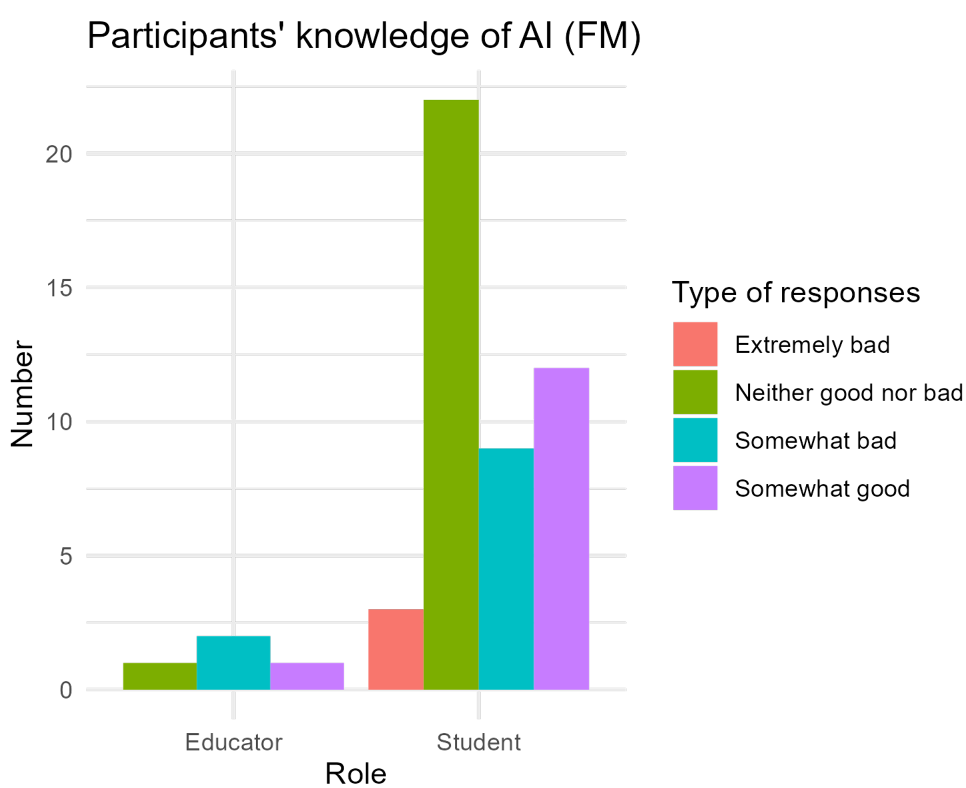


**Figure 3**

*AI knowledge.*

For Figure 4 about the machine learning and deep learning there is it can be noticed that the majority of the participants (both educators and students combined) have answered with "Somewhat agree" and also not small part of the students have respondents with "somewhat disagree" and "strongly disagree". Also, from the 3 educators, who have answered, 2 of them have put "somewhat disagree" as an answer.

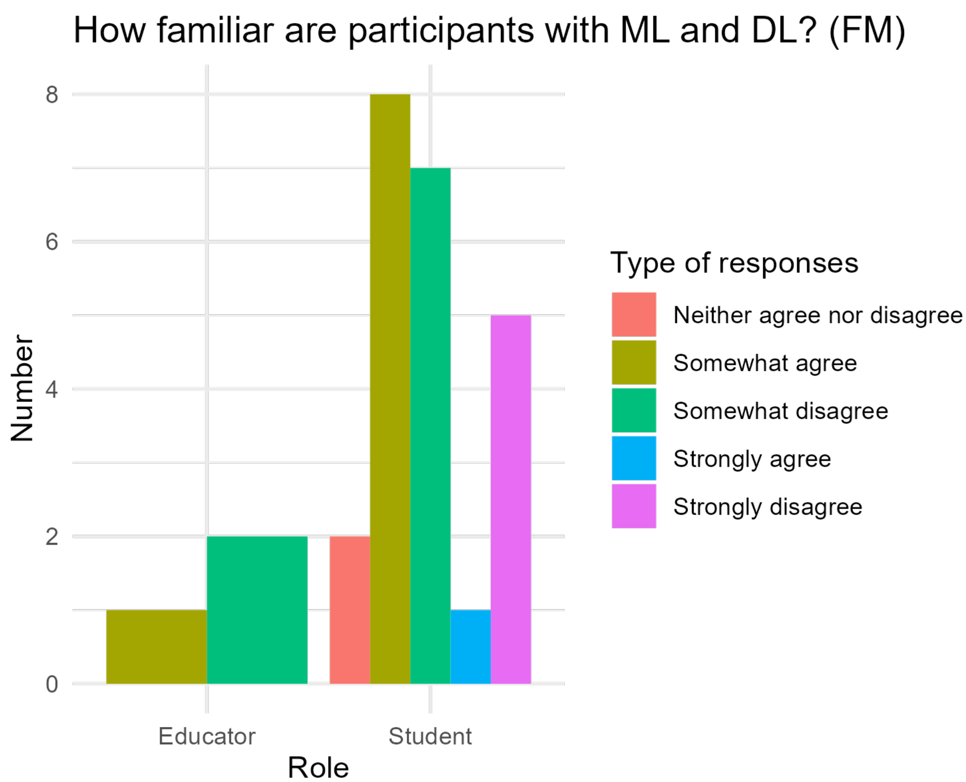


**Figure 4**

*ML and DL familiarity.*

Also, the participants were asked which component of facility management will play an important role. Based on the responses, energy efficiency is with the highest number of 22 and right after it is predictive maintenance, which is with 21. Then are security and space optimization with 18 and 16 respectively. With the least answers is the option "Other (please specify)" as the number there is 4(This can be seen in Figure 5).

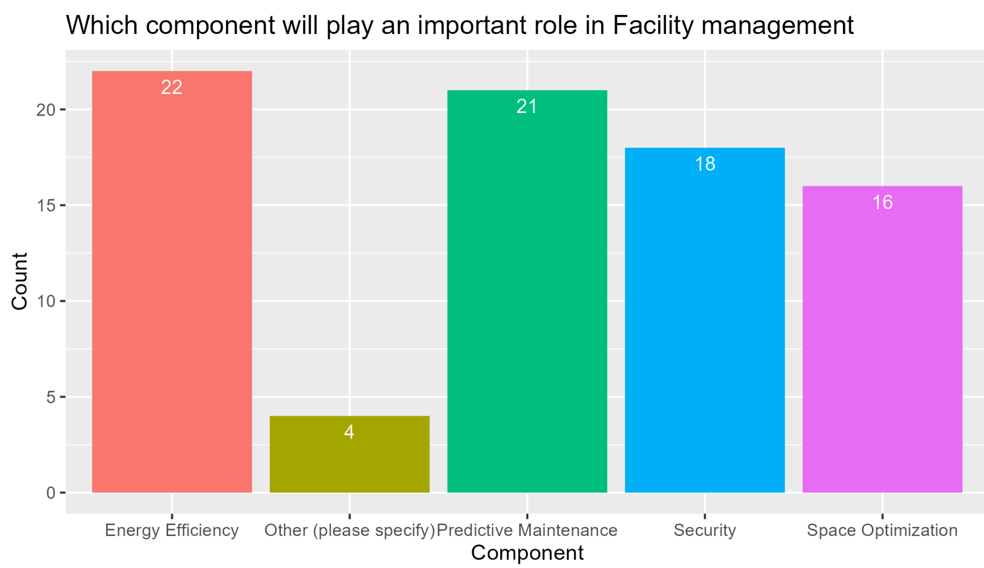


**Figure 5**

*Key components in FM.*

For the quantitative part of the project, there were 3 research questions, to be answered to as each are focused on different analysis - descriptive analysis, t-test and linear regression.

***Descriptive analysis***

This section is focused on a descriptive analysis, which was done on the data. It tries to answer to the question "What is the potential impact of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas on academic performance and skill development of students". To be answered this question, in the survey there was a separated section, which was specifically made for predictive maintenance. In figure something it can be noticed that the best way to get closer to predictive maintenance is through Real-world case studies as there are 8 answers. Then is interactive workshops and online simulation with small difference - 7 and 6 respectively. The least chosen option is AI-powered virtual labs. The question was multiple option, so the participants can put more than.

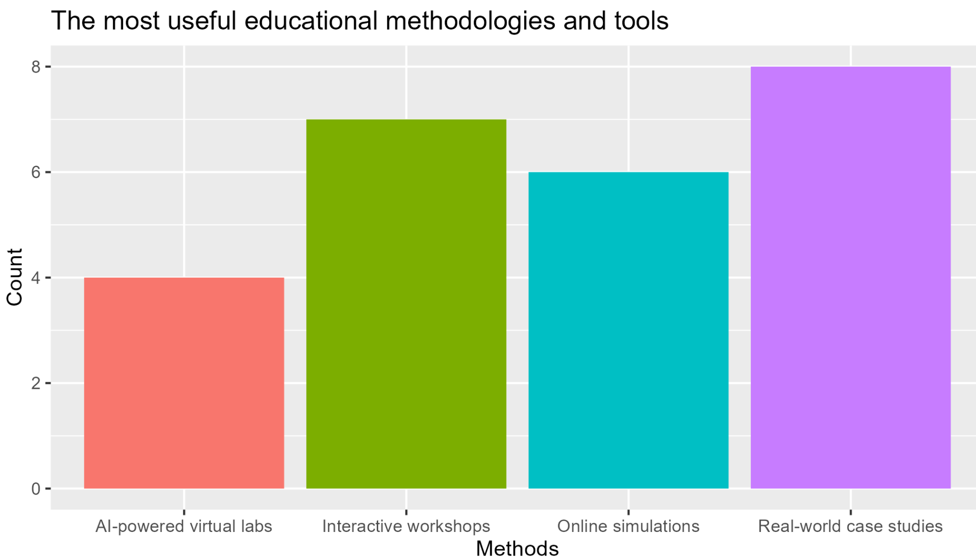


**Figure 6**

*Educational methods and tools.*

The other 4 questions are based on the likert scale (1-5). Based on figure number something, it answers for the question whether predictive maintenance (PM) is included in the curriculum, 5 of the respondents have answered with "to a minimal extent", while 3 of them have answered with "to a significant extent". The second graph about the impact on the skill development it shows that 6 people believe that it is "very effective", while the rest each have 2 responses ("highly effective" and "moderately effective"). The majority of the participants (6) believe that predictive maintenance can improve facitily management skills "very much" and one believe "extremely". The rest have responded with "moderately" (3) and "slightly" (1). The last question is more of a side one as it was asked are there ethical considerations integrated in PM. Most of the answers point to the conclusion that is "somewhat" integrated as there is also one disagreement.

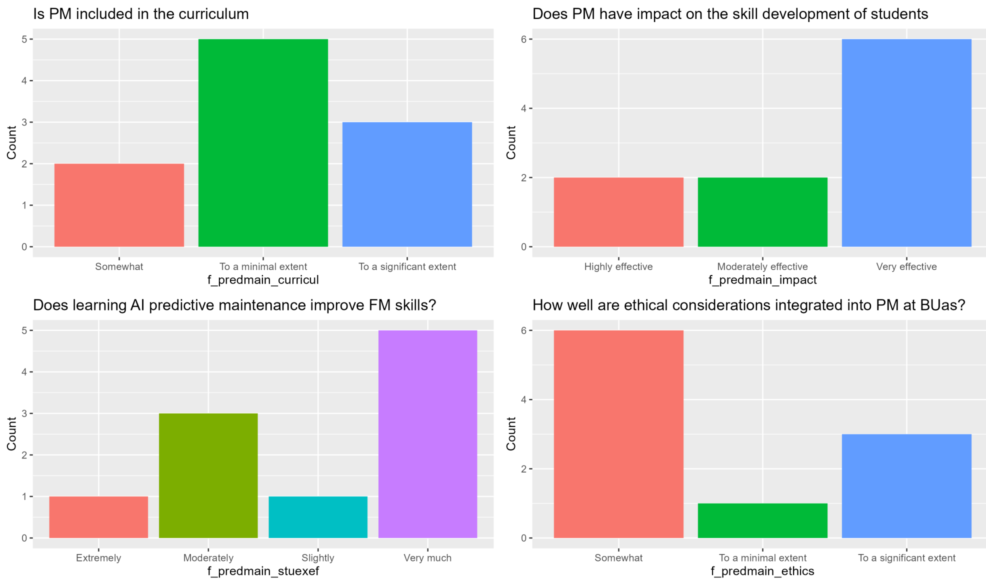


**Figure 7**

*Survey answers.*

### *T-test*

To be answered the second quantitative question of the research, which is "What is the measurable effect of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas on the skill development of students?", it was performed one sample t-test. This is a statistical method used to determine if the mean of a single sample is significantly different from a specified population mean. So it can be performed, before that there were two hypothesis created (Null and alternative). The former is "The mean impact rating of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas is equal to a specific value." and the latter is "The mean impact rating of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas is not equal to a specific value." It was taken the variable f_predmain_stuexef, which represents the perceived extent to which students' exposure to AI-based predictive maintenance techniques in their coursework enhances their ability to effectively apply these techniques in practical facility management scenarios. It was set hypothesized value (population mean) to 4, which can be also considered as "agree". The results can be seen below.

| | |
|---|---|
| Data: | pm_num_data$f_predmain_stuexef |
| | $t = -1.5, \quad \mathrm{df} = 9, \quad \text{p-value} = 0.1679$ |
| Alternative Hypothesis: | True mean is less than 4 |
| 95% Confidence Interval: | $(2.996758, 4.203242)$ |
| Sample Estimates: | |
| Mean of $x = 3.6$ | |

As it can be noticed, the p-value is 0.1679, which is higher than 0.05. The t-value of -1.5 indicates that the sample mean is 1.5 standard errors below the null hypothesis mean. The degree of freedom is "spent" estimating the mean, which is n-1 as in my case is 9, since n is 10. The 95% confidence interval is between 2.996758 and 4.203242, which means the hypothesis cannot be rejected between this range. Furthermore, the effect size was measured, so it can be seen the difference between the sample mean and the population mean as it was used Cohen's d. It ended up being -0.4743416, which means the mean of the first group is smaller than the second (population mean). Additionally, it helped for performing of the power analysis.

Overall, based on the results it can be concluded that there is not enough evidence to reject the null hypothesis.

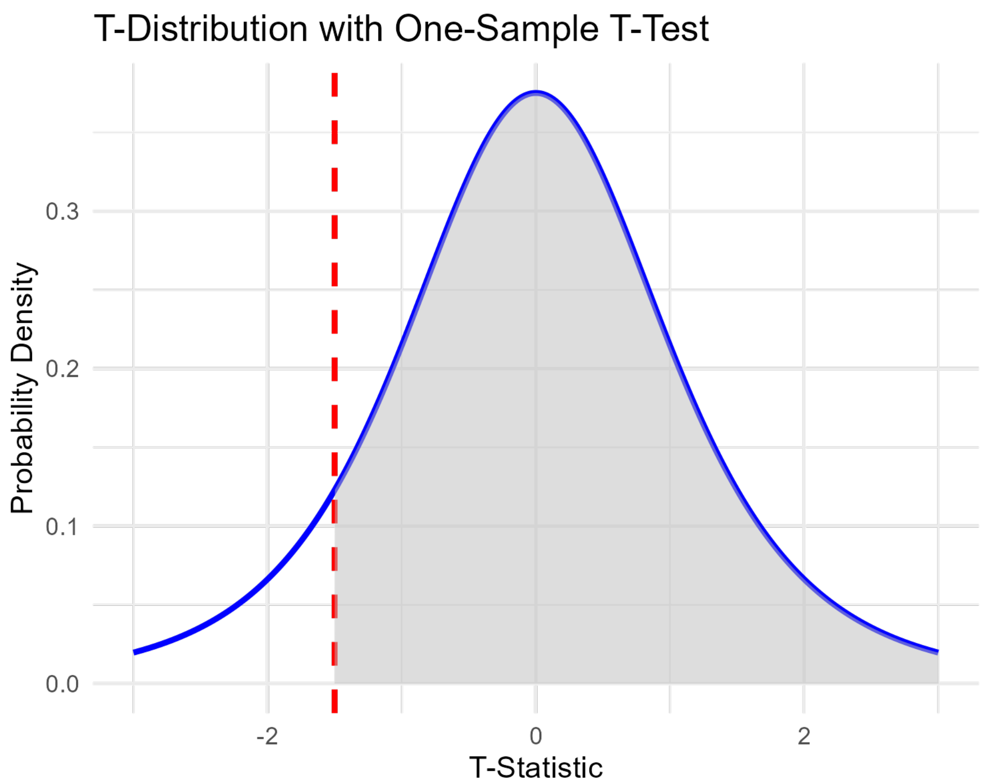


**Figure 8**

*T-test distribution.*

***Linear regression***

This section is going to be focused on the hypothesis that there is no significant relationship between students' exposure to AI-based predictive maintenance techniques in their coursework and their ability to effectively apply these techniques in practical facility management scenarios. It was used linear regression on two columns - f_predmain_impact and f_predmain_stuexef. Since the latter variable was described in the previous section about t-test, the former represents the perceived impact of integrating AI-based predictive maintenance tools and methodologies into the facility management curriculum at BUas on the skill development of students. To make sure that there is some relation, it was checked the correlation coefficient between the both variables, which ended up being 0.39. That means it is positive and there is positive correlation between them and if one of the variables increases, the other will as well. Hence, it was implemented linear regression as below are the results.

Call: lm(formula = f_predmain_stuexef f_predmain_impact, data = pm_num_data)

Residuals:

$$\text{Min} : -1.100$$
$$\text{1Q} : -0.475$$
$$\text{Median} : 0.150$$
$$\text{3Q} : 0.400$$
$$\text{Max} : 1.400$$

Coefficients:

$$\text{Estimate} : (Intercept) = 1.6000, f_predmain_impact = 0.5000$$
$$\text{Std. Error} : (Intercept) = 1.6636, f_predmain_impact = 0.4108$$
$$\text{t value} : (Intercept) = 0.962, f_predmain_impact = 1.217$$
$$\text{Pr(>|t|)} : (Intercept) = 0.364, f_predmain_impact = 0.258$$

Residual standard error: 0.8216 on 8 degrees of freedom

$$\text{Multiple R-squared} : 0.1562$$
$$\text{Adjusted R-squared} : 0.05078$$
$$\text{F-statistic} : 1.481 on 1 and 8 degrees of freedom$$
$$\text{p-value} : 0.2582$$

The linear regression model using ’f_predmain_impact’ as a predictor is not very reliable. It only explains about 15.62% of the differences in ’f_predmain_stuexef’, which means it is not great at telling us why things are different. Then, we look at the leftover differences between the predicted values and the actual ones (the residuals), they vary quite a bit, showing that the model cannot capture all the differences in the data. The model does not seem to be very useful overall, as the F-statistic is low, indicating it might not be meaningful. Furthermore, the p-value is above 0.05, so it cannot reject the null hypothesis. Also, the low R-squared value shows that there is data, which cannot be explained.

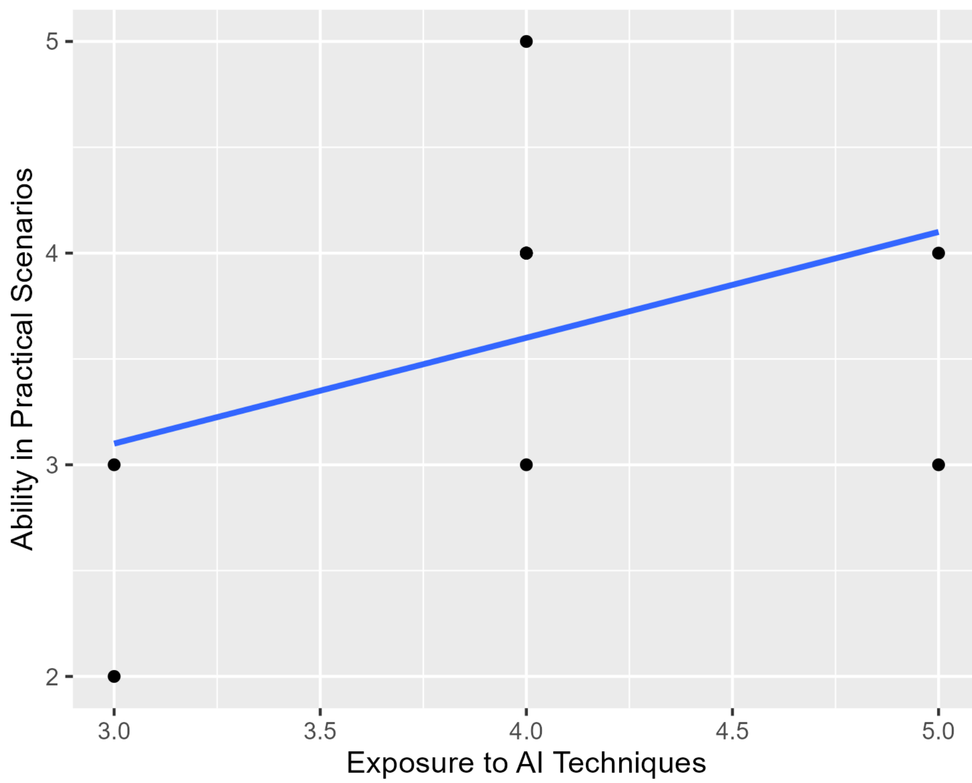


**Figure 9**

*Linear graph.*

**Qualitative findings**

Even though the quantitative data from the survey gives good idea of the people perspective of AI and predictive maintenance, it was needed to be done a qualitative research as well. This was possible by conducting interviews and by this way it could be given even deeper insights.

### *Interviews*

Semi-structured interviews were conducted by the group as we managed to find 5 participants as each member interviewed one person. All of us used the same interviews questions. The interview was separated into a few sections as there were general questions about AI and questions about each component of facility management - energy efficiency, predictive maintenance, space optimization and security.

However, two of the interviews were enough to provide a better understanding of how predictive maintenance can impact decision-making. Additionally, one of the participants had prior working experience in the field of predictive maintenance, while the other showed a strong interest in the area. Both participants believe that predictive maintenance will not only be more efficient than human, but will also lead to cost savings. Furthermore, it will impact scheduling for maintenance activities, which will improve strategic decision-making. One example mentioned by the participants involved placing sensors to detect when a specific area, such as painting, should be maintained. The other participant suggested using calculations to determine the optimal maintenance intervals, which would result in cost savings for that specific period - they gave an example about at what period of time should be a certain area cleaned.

The participants were also asked about ethical considerations in the context of predictive maintenance. One of the participants believed that this does not involve personal data, and therefore, any ethical concerns would be minimal. By contrast, the other participant believed that since everything can be sensor-based, it might involve the collection of personal information. Therefore, there are different points of view in terms of ethical considerations.

## Discussion

In this part of the report is presented the discussion of the findings. Firstly, the descriptive analysis gives the information that the majority of participants believe that AI and predictive maintenance will play big impact on their skills development and how to apply this knowledge in real-life situation. Also, they suggest that the most useful way to get to learn how to work with predictive maintenance is by participating in real-world case studies and interactive workshops. Furthermore, the t-test hypothesis (The mean impact rating is equal to a specific value.) cannot be rejected, since the result is not less that 5% (0.05). Also, the linear regression, which was implied for the hypothesis (There is no significant relationship between students' exposure to AI-based predictive maintenance techniques in their coursework and their ability to effectively apply these techniques in practical facility management scenarios) also cannot be rejected as the value is also higher than 5%. Moreover, the model is not really useful since the F-statistic value is low (1.481). Overall, the participants believe that there is positive impact in implementing predictive analysis in maintenance on their skills as they prefer specific as they prefer more practical educational methods. However, the statistical methods do not seem to be reliable and cannot provide strong evidence, I suggest that further research should be conducted or different models should be tried.

### Implications

The findings suggest that students prefer practical education in AI and predictive maintenance as based on the survey they put real-world case studies and interactive workshops as useful ways. However, the statistical analysis, while unconvincing, implies the necessity for more comprehensive research with refined models to establish a clear link between coursework exposure and practical application. This highlights the importance of adapting educational approaches to prepare students effectively for AI in maintenance.

### Recommendations

Based on the findings and their implications, it is recommended that Breda University of Applied Science and facility management program should prioritize experiential and practical learning opportunities in AI and predictive maintenance. This includes incorporating real-world case studies and interactive workshops into the curriculum. The students should be more exposed to predictive maintenance practices, so they can get prepared for the industry. Also, I recommend making further research about, since there was limitation of the data and the models used for hypothesis did not seem to be appropriate.

### Limitations

During the project the group encountered many limitations related to the collection of data. Firstly, it was hard to be found participants for the interview as we were lucky to find 5 volunteers. Secondly, for the survey there were only 50 respondents from the facility program as only 1/5 of them have responded to the questions related to predictive maintenance. Subsequently, this might have influenced the hypothesis testing to not be really efficient since there was not much data.

## Conclusion

Artificial intelligence will become part of our daily lives and this is inevitable. Thus, we have to learn to adapt to it as there will be benefits and drawbacks. However, facility management is going to be strongly affected by the entry of AI and the students should be prepared. Predictive maintenance is already integrated in the industry and it is expected to be widely used around the world in the future. The purpose of the research was to try to find out whether its usage is going to have impact of the decision-making not just in the industry, but in the education processes in the facility management program at BUas. This was answered by conducting a mixed-method research, consisting both qualitative and quantitative methods as interviews and survey were made for each respectively.

From the survey, we got 50 respondents from facility management and 1/5 of them answered to the questions related to predictive maintenance. The descriptive analysis showed that the participants believe PdM have impact of the skills development and if there is more exposure to it, this will improve their ability apply these techniques. Therefore, there should be more interactive workshops and real-world cases, so the students can gain more experience. However, the t-test and linear regression did not seem to be reliable as there can be two reasons - more data is needed or the models were unappropriate.

On the other hand, the qualitative research seemed to gave more information and deep insights for predictive maintenance. The participants believe that its impact of the decision-making will be significant it will help to reduce costs, energy usage and will improve the strategy in decision-making.

Overall, predictive maintenance is a component, which will going to change entirely the facility management field as it is going to improve its quality. To improve even faster, students should gain solid knowledge, which will enable them to implement it in the near future.

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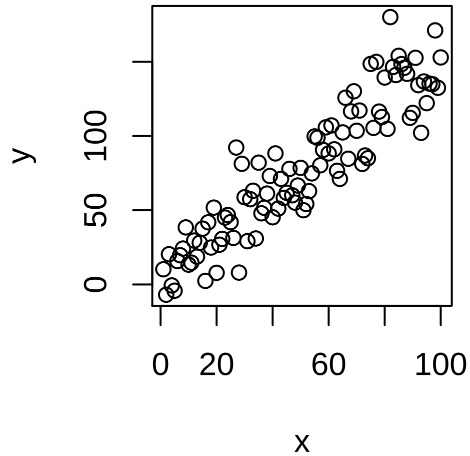
**Figure A1**

*This is my second figure caption.*




# Appendix

## Instrument

As shown in Figure A1, these results are impressive. Nulla ac nisl. Nullam urna nulla, ullamcorper in, interdum sit amet, gravida ut, risus. Aenean ac enim. In luctus. Phasellus eu quam vitae turpis viverra pellentesque. Duis feugiat felis ut enim. Phasellus pharetra, sem id porttitor sodales, magna nunc aliquet nibh, nec blandit nisl mauris at pede. Suspendisse risus risus, lobortis eget, semper at, imperdiet sit amet, quam. Quisque scelerisque dapibus nibh. Nam enim. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Nunc ut metus. Ut metus justo, auctor at, ultrices eu, sagittis ut, purus. Aliquam aliquam.