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# Influence of Higher Education on IoT Acceptance through Hands-On Learning

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***Abstract* – The Internet of Things (IoT) applications are pervasive across various sectors; however, there remains some resistance to its adoption. Education 4.0 promotes the full integration of new technologies, both as tools for learning and instruments for professional development. This work studies the influence of higher education on the willingness towards IoT adoption after hands-on learning experiences. The primary objective is to determine whether a correlation exists between IoT adoption and the education of university students from three distinct professional degrees. The methodology employed involves a practical class where students engage in developing applications for manual data collection. These applications are designed to send data to the Internet, which is then visualized through a web interface. Tailored to each respective degree, three similar applications are developed. For this research, M5 Stack Core2 kits are utilized, along with UIFLOW programming language and the ThingSpeak platform, operating under the MQTT protocol. Following the training, students complete a Technology Acceptance Model (TAM) survey for IoT. The analysis of the influence of higher education on IoT acceptance employs ANOVA to identify differences between group means.**

**The results reveal statistically significant differences in IoT acceptance between students in Industrial and Architecture degrees.**

***Keywords* – Technology acceptance model, IoT technology, higher education, hands-on learning.**

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## 1. Introduction

The Internet of Things (IoT) drives a digital transformation towards smart environments, connecting from simple devices to complex systems [1], [2]. This technological revolution materializes in a hyperconnected internet, where information flows between objects, generating, collecting, and utilizing data [3], [4], [5]. Based on wireless sensors and nanotechnology, IoT integrates circuits, software, and network connectivity [6], [7]. IoT creates a unique convergence between disciplines to establish a globally interconnected and smart environment [8]. This global network confers the ability to self-regulate, efficiently monitoring and controlling its environment [9], [10], [11]. IoT has experienced significant growth, improving forecasting, efficiency, and automatic rebooting, reducing times, accelerating, and minimizing processes [12]. IoT is a versatile and powerful tool, applicable in future cities, smart homes, security systems, efficient energy consumption, and is applicable in the educational field.

Currently, educational institutions require training students in Science, Technology, Engineering, Arts, and Mathematics skills, integrating them into the curriculum, pedagogy, and evaluation techniques [13]. Leveraging the economical accessibility of hardware, the open-source nature of software, with educational approaches [14], 15]. The incorporation of IoT into teaching and learning processes represents an innovative component, aligning with the concept of hyper-situating with Education 4.0 [13], [16], [17]. IoT facilitates the convergence of technology with various disciplines through the use of specialized mobile devices, generating interactive, practical, and meaningful learning experiences. In education, IoT is a tangible application in everyday life that facilitates and enhances knowledge, improving students' skills towards a smart learning society [18], [19].

The IoT redefines the educational paradigm by transforming how students acquire knowledge, but its scope extends beyond the classroom. This educational revolution also shapes how professionals interact with their environment. Thus, IoT becomes a connected fabric across all professions, driving efficiency, innovation, and continuous adaptation in the contemporary workforce [20]. This technology proves to be a valuable resource in various degrees, spanning engineering, architecture, medicine, and education, enhancing performance and competitiveness [9], 10].

In the degree of industrial engineering, the application of IoT enables practical applications such as monitoring and predictive maintenance of industrial machines and equipment. It integrates embedded sensors that collect data, allowing for process optimization, inventory and logistics management, energy efficiency improvement, and workplace safety through environmental conditions. Furthermore, it enhances product quality during the manufacturing process, analyzes data, automates, and remotely controls [21], [22].

For the degree of Architecture, IoT provides improvements in efficiency, sustainability, and user experience. With this technology, smart buildings can be managed, where connected sensors control systems, optimize energy efficiency [23], [24], enable structural monitoring, design based on data, manage waste by providing information to containers, and examine physical variables such as temperature, humidity, air quality, light, and sound [25], [26]. In architecture, the tools offered by IoT allow for the design of more user-centered efficient environments.

In the degree of medicine, IoT enables significant improvements in remote monitoring of patients with chronic diseases or health conditions that require continuous monitoring. This technology efficiently manages hospital resources, monitors them, anticipates problems, and optimizes use. IoT efficiently brings real-time medical data from a patient, prevents diseases through early diagnosis to improve the patient's quality of life [5], [27]. IoT in medicine is applied in teaching processes at universities. Edutech technology in medicine effectively contributes to personalized, efficient teaching [28], [29]. With educational digital transformation applied to medicine, industry, architecture and education, experiences are meaningful for university students.

The objective of this research is to evaluate the influence of higher education on the acceptance of IoT technology through hands-on learning. For this purpose, three groups of university students receive a practical IoT class, developing an application related to their study degree. Evaluation is done through student performance in class and a TAM of IoT, which undergoes statistical analysis to determine significant differences through ANOVA.

This document is organized as follows: Section 2 presents the related studies; Section 3 describes the materials and methods used; Section 4 presents the results obtained; Section 5 details the discussion; and Section 6 presents the conclusions of this research.

## 2. Related Works

It is crucial to highlight that, during the literature review, no studies were found with the same purpose as the one proposed in this research. Consequently, related works that address the acceptance of IoT technology in various fields or from different perspectives are examined.

Literature can help discern the acceptance of IoT within a region or country. [30] explores the key factors influencing IoT adoption in Saudi Arabia, drawing insights from existing literature. It highlights significant areas of IoT acceptance, including industry, agriculture, livestock, education, healthcare, smart cities, and personal management with IoT-enabled wearable devices. The study also addresses challenges such as IoT security and privacy risks, trust, costs of devices and components, scalability, standardization, and issues related to data collection and storage. Additionally, consumer input is emphasized as critical for understanding technology acceptance. Reference [31] examines the determinants of consumer acceptance of smart meters in Brazil, offering insights to inform public policies supporting smart meter deployment. The research, based on the UTAUT2 model, involved a survey of 144 participants from a Brazilian city. It identifies social influence as a major driver of smart meter acceptance, while notably finding that performance expectancy has little to no impact.

The objective of the research goes beyond measuring IoT acceptance; it is necessary to identify if other areas of knowledge are willing to adopt IoT. [32] extends the theory of individual ambidextrous learning and incorporates UTAUT to create a quantitative model examining professional learning behavior related to rapidly evolving digital technologies in IoT. A structured survey was conducted with 685 professionals from 95 companies in India, spanning the automotive, aerospace, healthcare, and energy sectors. The study reveals that factors such as social influence, personal innovation, anxiety, long-term consequences, and job relevance shape the behavioral intention to learn about IoT. The research also considers professional performance levels and technological preferences. For top-performing professionals, personal innovation emerges as the primary driver of learning intentions, whereas for average-performing individuals, social influence and anxiety also play significant roles.

Furthermore, to achieve IoT acceptance in higher education, teachers must initiate this transformation. [33] aimed to investigate university professors' acceptance of IoT for its potential future integration into higher education. An online survey, grounded in the UTAUT framework, was conducted with 587 Spanish university professors aged between 21 and 58. The findings revealed that performance expectancy, facilitating conditions, and attitudes toward technology use significantly influenced their behavioral intention to adopt IoT. Participants demonstrated a high level of IoT acceptance and a favorable disposition toward its future application. Consequently, the study highlights the need for educational institutions to invest in integrating IoT resources into universities, presenting a transformative opportunity for the academic system and its professionals.

In the context of this study, students from different degrees must indicate their stance on IoT acceptance. [34] focuses on identifying the key factors influencing students' intention to adopt IoT technologies in Saudi Arabian higher education institutions. The study employs a TAM-based approach, incorporating external factors such as knowledge exchange, mobility, interactivity, innovation, training, and virtual reality. A questionnaire targeting students exposed to various IoT applications and services within a higher education setting was used to validate the model. Findings from the structural model evaluation and regression analysis indicate that all factors are significant and positively impact IoT adoption. [35] analyzes the technological readiness of university students through an online questionnaire oriented towards Generation Z to determine their intention to adopt IoT in the online educational context. Results reveal that technological optimism, discomfort, and individual insecurity affect their intentions to adopt IoT products and services for online learning, while the motivational factor and innovation, have an insignificant impact. Findings are oriented towards designing products and strategies to promote online learning and implement educational IoT.

Finally, the aim of [36] is to test an IoT model of IoT technology acceptance among economics students in Romania. The study involved 1,179 students from four university centers in Romania, with the IoT-related factors in the TAM framework analyzed using SPSS. The analysis included reliability and validity tests, chi-square tests, and Pearson correlation coefficients. The findings revealed a positive correlation, suggesting that economics students are ready to embrace new IoT technological advancements and apply them in their future careers.

No work was found involving non-technical degrees students as application developers prior to assessing IoT technology acceptance. Furthermore, none compare these results to determine the influence of higher education on technology adoption. To the best of the authors' knowledge, this is the first work proposing an analysis of this kind, significantly contributing to the behavioral understanding of IoT acceptance and creating new possibilities for future research.

## 3. Materials and Methods

The objective of this research is to determine if higher education influences the acceptance of IoT. Thus, the research is designed in 5 stages, as shown in Figure 1. In the first stage, students from three different higher education degrees are selected. In this case, the degrees are Medicine, Industrial degree and Architecture. In the second stage, students undergo a practical IoT class, where they develop an application related to their degrees. The training is based on hardware and software platforms that facilitate learning. In stage 3, student performance in the class is evaluated by a teacher in three components: execution time, motivation to learn, and performance of the developed application. In stage 4, a validated TAM is applied in the context of IoT based on 7 factors. Finally, in stage 5 of the study, statistical analysis is conducted to determine if there is a significant difference in the acceptance of this technology among student groups.

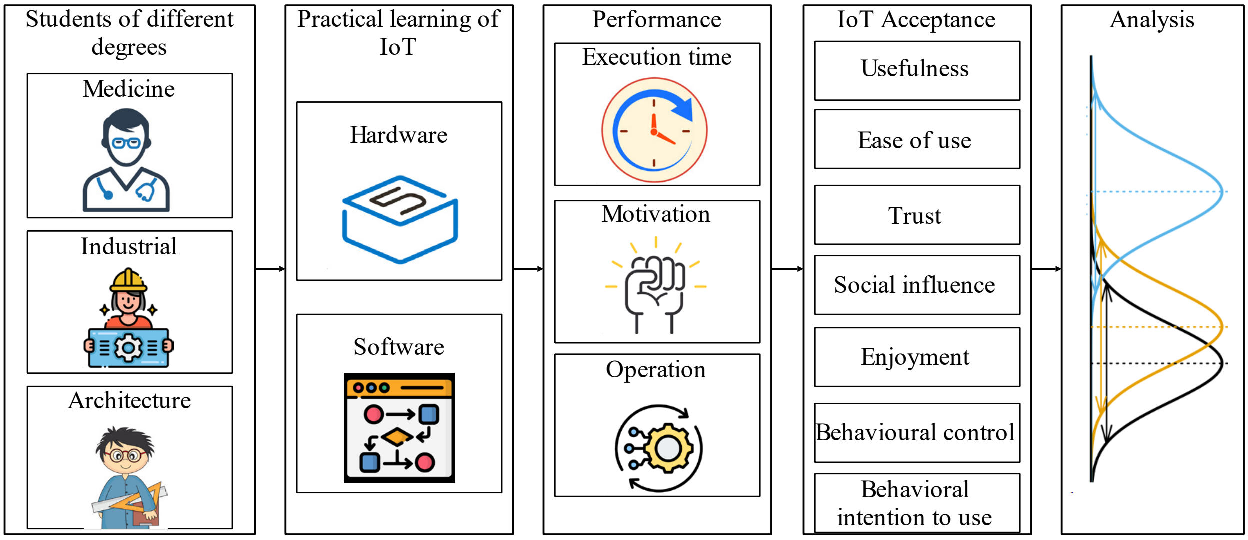


*Figure 1. General outline of the research*

### *3.1. Hardware*

In the current market, there is a wide variety of hardware platforms available for getting started in IoT application development. However, for this study, it is important that the equipment is easy to use, as it involves students from the Medicine and Architecture degrees, who do not have related previous training. The options considered were as follows:

ESP32-WROOM-32: This module is a microcontroller based on the ESP32 chip, featuring built-in Wi-Fi and Bluetooth capabilities. It supports a wide variety of peripherals, including capacitive touch sensors, an SD card interface, Ethernet, high-speed SPI, UART, I2S, and I2C [37]. The average cost of this device is $6 in the U.S.A., making it the cheapest option. Although this option is convenient, it requires additional circuitry for application development.

Particle Argon: This Wi-Fi development kit features Nordic's nRF52840 and Espressif's ESP32 processors. It comes with an integrated battery charging circuit for easy connection to a Li-Po battery and provides 20 mixed-signal GPIOs for interfacing with sensors, actuators, and other electronic components [38]. The average cost of this device is $75 in the U.S.A., making it the most expensive option. This option is very powerful for developing complex IoT applications but requires additional circuitry for application development.

M5 Stack Core2: It is a kit built around the ESP32, featuring Wi-Fi connectivity, a USB Type-C interface for charging its built-in 390 mAh battery, programming downloads, a serial port, a 2.0-inch capacitive touchscreen, power and reset buttons, and various additional integrated components [39]. The average cost of this device is $45 in the U.S.A., making it the middle option for this case.

This option does not require additional circuitry for application development as it includes a touchscreen interface, and it is the selected option for this research, acquiring 20 devices for individual practices with the students.

### *3.2. Software*

An additional advantage of the selected hardware platform for practical IoT teaching is its ability to be programmed in both text-based languages (C++ and Python) and block-based language. In this research, using block-based language is advantageous due to its high intuitiveness and quick learning curve. The M5 Stack Core2 is programmed in blocks using the UIFLOW software, available in both web and desktop versions. For this study, the desktop version was installed on the 22 computers in the computing laboratory designated for hands-on classes with Windows 10 Professional operating system.

The application to be developed in the class consists of a manual state reporting system based on the students' degrees, with automatic responses related to those states. Medicine students report on the mood states of patients, such as sadness, happiness, anxiety, and stress. Industrial Engineering students report on states related to industrial safety in facilities, such as improper use of attire, electrical hazards, lack of ergonomics, and flammability. Architecture students report on states in the construction of a building, such as material intake and output, undesired weather conditions, and accidents. These applications were designed in collaboration with expert faculty members in each degree.

For the application development, ThingSpeak server is used as the communication platform via the MQTT protocol.

ThingSpeak was chosen for its ease of setup and user-friendly interface, while the MQTT protocol acts as a messenger communicating endpoints through topics.

Figure 2 shows the user interface and the block-based program in the UIFLOW environment. The user interface includes buttons for the states and a space for receiving messages.

The block-based program consists of three components: First, connecting to the network using Wi-Fi credentials and connecting to the ThingSpeak MQTT broker; second, publishing to the MQTT topic through ThingSpeak fields with a quality of service of 2; and third, subscribing to the MQTT topic to receive the suggestion code.

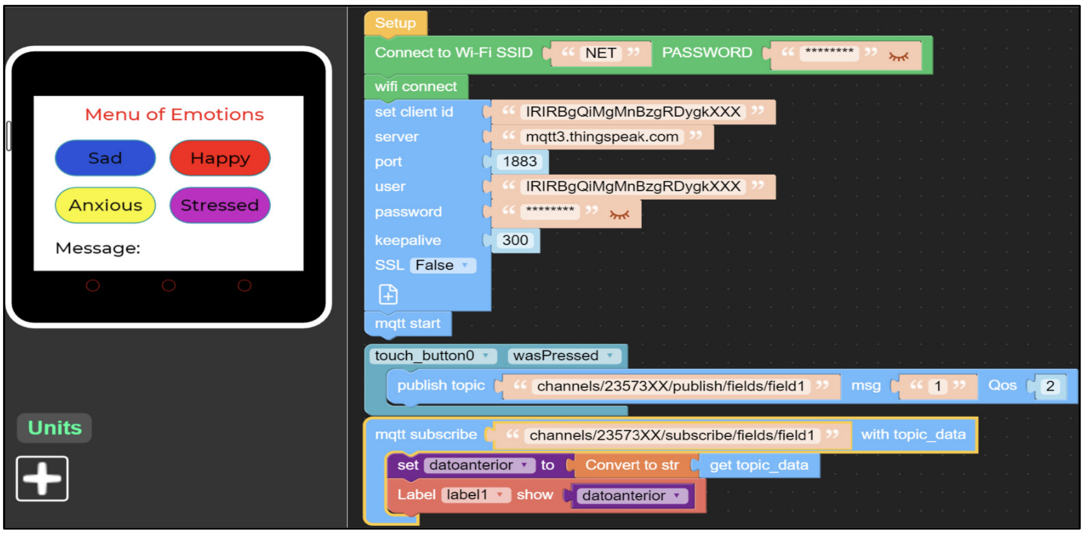


*Figure 2. Block program in UIFLOW for IoT class*

### *3.3. Intervention Design*

The interventions with students from the three degrees are conducted according to the design outlined in Figure 3. Initially, the class objective is presented, and demographic data of the participants are immediately collected through an online form. Prior to the practical session, a brief theoretical introduction is given to explain important definitions for the classes.

Following this, the development of applications with the students commences. Once the applications are completed, functionality tests are carried out. Throughout the class, several teachers provide support to the students and assess their performance. Pre-intervention tests were conducted with another group of students to determine an approximate class duration of 125 minutes. Finally, the students respond to the indicators of a TAM via an online form, facilitating the collection of results.

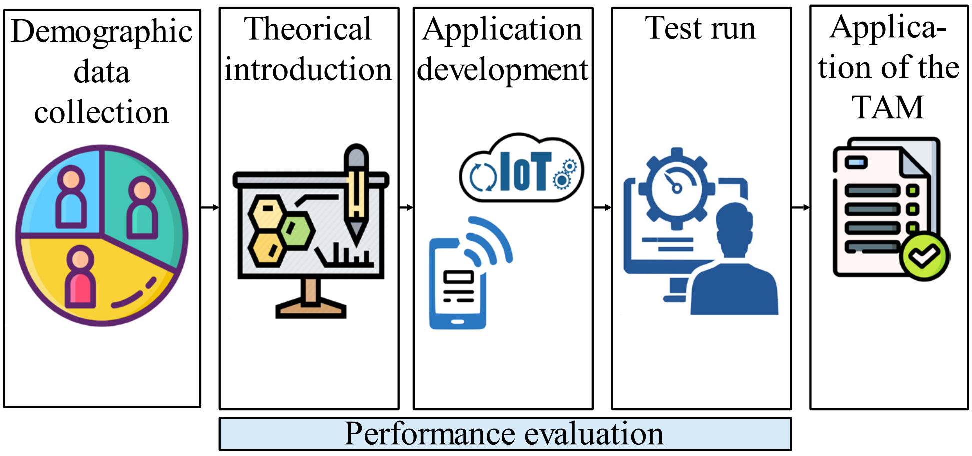


*Figure 3. Intervention design.*

### *3.4. Participants*

The participants were selected from a private university at the highest possible educational levels.

The Medicine program is new at this university, so it only had up to the 5th semester; in this group, there are 14 participants with valid data.

The Architecture program encompasses all levels in the university, so this study worked with the 9th semester; in this group, there are 20 participants with valid data. The Industrial Engineering program also covers all levels, but this study had to select the 4th semester because in higher levels, students received IoT-related content, which could affect the results of this group. In this group, there are 8 participants with valid data.

Table 1 presents the demographic data of the students, including age, gender, access to technology, and interest in learning IoT.

Participants in the Medicine and Industrial Engineering programs had similar ages, while those in Architecture were older on average, as they were in their final semester.

Regarding gender, females predominate in the Medicine program, and males predominate in the other programs. Access to technology is measured based on the number of mobile devices they own (computer, smartphone, smartwatch, etc.), where Industrial Engineering students have fewer devices compared to the other programs. Finally, interest in learning this technology was collected based on a 7-level scale, ranging from -3 (completely disagree) to 3 (completely agree), showing that the Architecture program has the lowest interest in learning IoT, although it has a high standard deviation (SD).

*Table 1. Demographics of study participants*

| Medicine (N=14) | | Industrial (N=8) | |
|---|---|---|---|
| **Demographics** | **Value** | **Demographics** | **Value** |
| Education: | | Education: | |
| Level | 5 | Level | 4 |
| Age | | Age | |
| Mean | 21.41 | Mean | 21.66 |
| SD | 1.58 | SD | 2 |
| Gender: | | Gender: | |
| Male | 5 | Male | 8 |
| Female | 9 | Female | 0 |
| Other | 0 | Other | 0 |
| Technology | | Technology | |
| Mean | 3.14 | Mean | 2.5 |
| SD | 0.99 | SD | 0.71 |
| Interest | | Interest | |
| Mean | 2 | Mean | 2.63 |
| SD | 1.2 | SD | 0.48 |
| **Architecture (N=20)** | | | |
| **Demographics** | **Value** | **Demographics** | **Value** |
| Education: | | Technology | |
| Level | 9 | Mean | 2.9 |
| Age | | SD | 0.77 |
| Mean | 24.78 | Interest | |
| SD | 2.48 | Mean | 0.85 |
| Gender: | | SD | 2.2 |
| Male | 14 | | |
| Female | 5 | | |
| Other | 1 | | |

### *3.5. Instruments*

For this research, two data collection instruments are utilized: One to assess the participants' performance and another to gauge technology acceptance. The evaluation of participants' performance in the IoT hands-on class is based on three components, as depicted in Table 2.

Each indicator offers five levels of possibility, and a mean is assigned according to a performance scale where 1 corresponds to "Very bad" and 5 corresponds to "Very good."

Performance evaluation is conducted by several instructors, ensuring each group of four students is assessed by a different instructor to ensure adequate performance control.

*Table 2. Scale for evaluating student performance*

| Indicator | Scale | | | | |
|---|---|---|---|---|---|
| Time execution | Very slow | Slow | Regular | Fast | Very fast |
| Motivation | Very discouraged | Discouraged | Regular | Lively | Very Lively |
| Operation | Very nonfunctional | Nonfunctional | Regular | Functional | Very Functional |
| **Performance (Mean)** | **Very bad** | **Bad** | **Regular** | **Good** | **Very good** |

To assess acceptance, the validated instrument from [40] is utilized. This study proposes an IoT Acceptance Model consisting of three technological factors (PU, PEOU, and TR), one social context factor (SI), two individual user characteristics (PE and PBC), and one additional factor (BI). The 25 indicators of the TAM were tailored for the research, as depicted in Table 3.

*Table 3. IoT acceptance model indicators*

| ID | Indicator | ID | Indicator |
|---|---|---|---|
| **Perceived usefulness (PU)** | | **Trust (TR)** | |
| PU1 | Using IoT would enable me to collect data more quickly. | TR1 | IoT is trustworthy. |
| PU2 | Using IoT would make it easier for me to make more efficient decisions. | TR2 | IoT provides reliable. information. |
| PU3 | Using IoT would significantly reduce my time collecting data. | TR3 | IoT keeps its promises and commitments. |
| PU4 | In general, I would find using IoT to be advantageous. | TR4 | IoT keeps my best interests in mind. |
| **Perceived ease of use (PEOU)** | | **Social influence (SI)** | |
| PEOU 1 | Learning to use IoT is easy for me. | SI1 | People who are important to me would recommend using IoT. |
| PEOU 2 | I find my interaction with IoT clear and understandable. | SI2 | People who are important to me would find the use of IoT beneficial. |
| PEOU 3 | I think using IoT is easy. | SI3 | People who are important to me would find using IoT a good idea. |
| **Perceived enjoyment (PE)** | | **Behavioral intention to use (BI)** | |
| PE1 | I have fun using IoT. | BI1 | If I give a chance, I intend to use IoT. |
| PE2 | Using IoT is pleasurable. | BI2 | I am willing to use IoT in the near future. |
| PE3 | Using IoT gives enjoyment to me. | BI3 | I will frequently use IoT. |
| **Perceived behavioral control (PBC)** | | BI4 | I will recommend IoT to others. |
| PBC1 | The use of IoT is entirely within my control. | BI5 | I will continue using IoT in the future. |
| PBC1 | I have the resource, knowledge and ability to use IoT. | | |
| PBC1 | I am able to skillfully use IoT. | | |

### *3.6. Statistical Methods*

The objective of the statistical methods is to determine statistically significant differences in the mean acceptance scores of each student grouped according to their study degree. Box plots are used for dispersion analysis, and quantile-quantile plots are employed for normal distribution analysis. Specifically, normality analysis is conducted using the Shapiro-Wilk method for each dataset. Homogeneity of variances tests is performed using the Fligner-Killeen and Levene's methods. Analysis of mean differences is carried out using the one-way ANOVA method for Welch's independent data. Pairwise comparisons are made using the T test and Benjamini and Hochberg adjustment method. These statistical methods were applied with a significance level of $\alpha=0.05$. All analyses were performed using R (version 4.3.2), with the functions utilized detailed in Table 4.

*Table 4. Statistical methods and functions used in r software*

| Analysis | Method | Functions |
|---|---|---|
| Dispersion | Box plot | ggplot, geom_boxplot |
| Distribution | Quantile-Quantile Plot | qqnorm, qqline |
| Normality | Shapiro-Wilk | shapiro.test |
| Homogeneity of variances | Fligner-Killeen and Levene's | fligner.test, leveneTest |
| One-way ANOVA for independent data (not assuming equal variances) | Welch | oneway.test |
| Comparison of significant difference between pairs. | T test, Benjamini and Hochberg | pairwise.t.test |

## 4. Results

The classes proceeded smoothly on three different dates in the laboratory assigned by the university, where the UIFLOW software was installed, and the various credentials for MQTT communication were stored. Out of the 45 participants involved in the experiments, 3 were excluded due to errors in the provided information, resulting in data analysis with the 42 valid participants, as outlined in the participant section above.

### *4.1. Performance*

Figure 4 presents the student performance results by degree. The Medicine degree has a mean of 3.5 out of 5, which represents a performance of 70%, although it has 2 students with a grade of 2 out of 5. The Industrial degree has a mean of 4.5 out of 5 and the Architecture degree has a similar mean. of 4.4 out of 5. In both degrees the median and mode is 5, obtaining a good performance in these degrees.

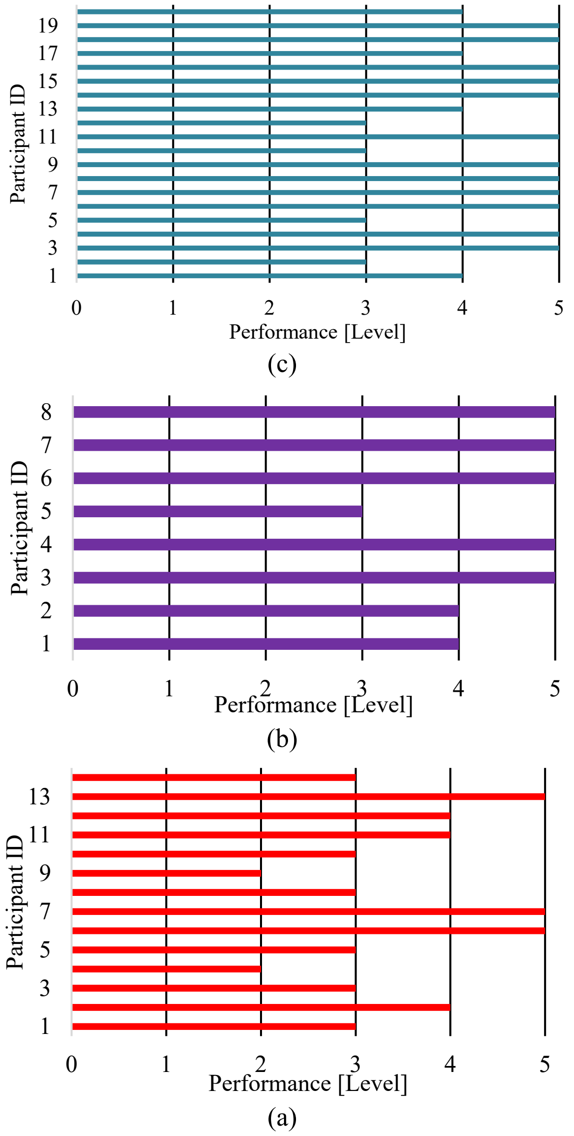


*Figure 4. Results of the students' performance evaluation in the IoT classes: (a) results of the Medicine degree; (b) results of the Industrial degree.; (c) results of the Architecture degree*

### *4.2. Acceptance*

Figure 5 presents the acceptance results by degree in the 25 TAM of IoT indicators. In all factors, the industrial degree has the greatest acceptance with the following means:

PU=82.29%, PEOU= 55.55%, TR=64.58%, SI: 81.94%, PE=70.83%, PBC=56.94%, and BI= 81.67%.

The worst acceptances are found in the Architecture degree with means of PE=23.33% and PBC=26.67%.

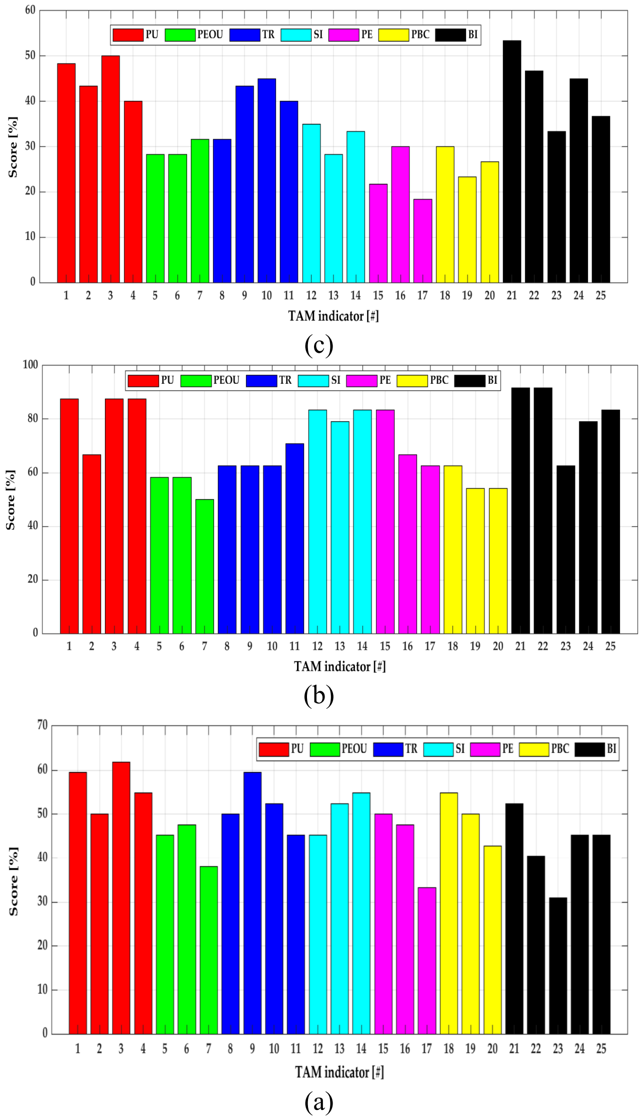


*Figure 5. TAM of IoT results: (a) results of the Medicine degree; (b) results of the Industrial degree; (c) results of the Architecture degree*

Finally, the results of the TAM by indicators are compared in a radial graph, as shown in Figure 6. The graph shows that the greatest acceptance is found in the Industrial degree with a mean acceptance of 71.76%, the second-best acceptance is found in the Medicine degree with a mean acceptance of 48.38%, and the lowest acceptance is found in the Architecture degree with a mean acceptance of 35.67%. In general, only the acceptance of the Industrial degree is suitable, the other degrees do not accept IoT technology.

### *4.3. Statistical Analysis*

The statistically significant difference between the mean acceptance scores of the students of the 3 degrees is required to be analyzed. In this case, a one-way ANOVA method with independent data is necessary. Begin by using box plots to to analyze the dispersion of the scores assigned by the students, as shown in Figure 7. Where different dispersions are evident, with a greater dispersion for Architecture students, close means and 3 outliers are also evident in the Medicine students.

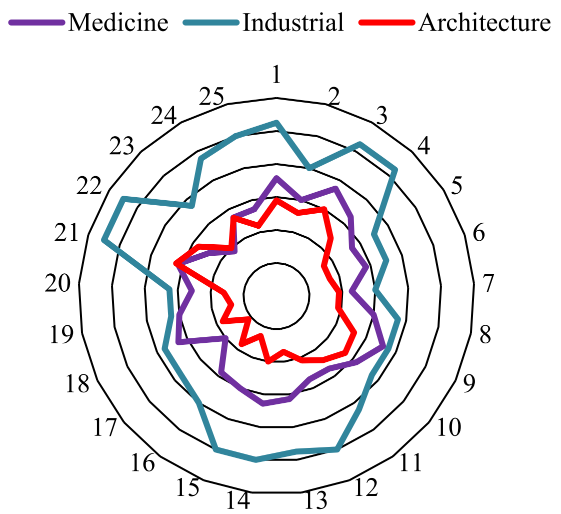


*Figure 6. Comparison by degree of the results for the 25 indicators of the IoT acceptance model*

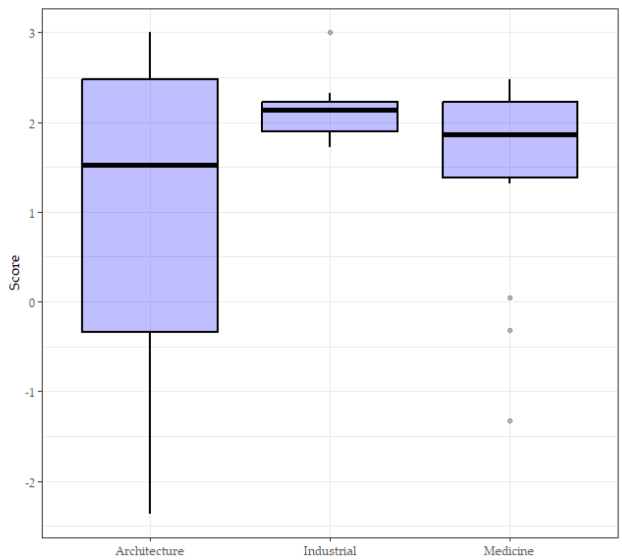


*Figure 7. Box plot of scores in the TAM of IoT by degrees*

To select the type of ANOVA, it is necessary to determine normality and homogeneity of the 3 groups of data. For normality analysis, a quantile vs quantile Plot is carried out, according to Figure 8, where all groups present some dispersion at the ends of the line, with greater dispersion in medical students.

To confirm normality, the analysis is complemented by applying the Shapiro-Wilk test for each data group because the amount of data in each group is less than 50, the results are presented in Table 5. These results confirm normality in the Industrial and Architecture data, while the p-value of Medicine is less than α, which shows evidence of lack of normality.

*Table 5. Results of normality tests using the Shapiro-Wilk test*

| Degree | W | p-value |
|---|---|---|
| Medicine | 0.80667 | 0.006042 |
| Industrial | 0.87928 | 0.1854 |
| Architecture | 0.90454 | 0.05021 |

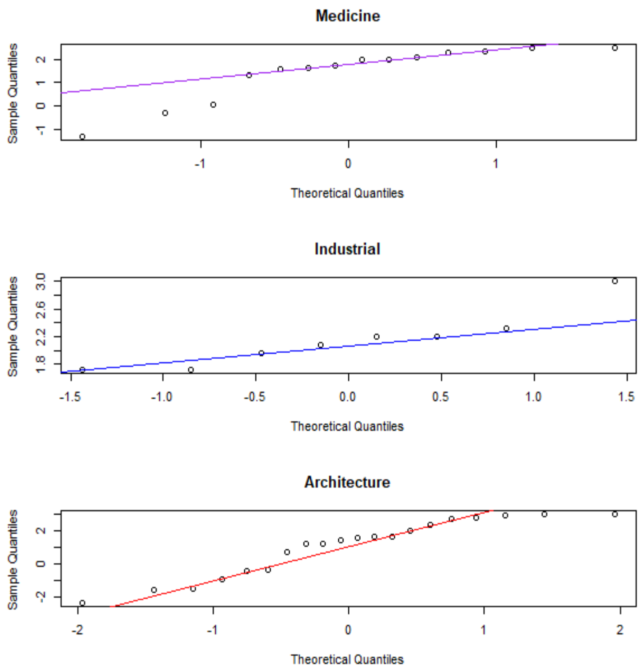


*Figure 8. Quantile-quantile plot of scores in the TAM of IoT by degrees*

On the other hand, the homogeneity of variances test is carried out between the study groups. Because the normality results are at the acceptance limit and there is a case of non-normality, the Fligner-Killeen and Levene's tests are applied. These results are presented in Table 6, where both p-values (<α) agree that there is significant evidence of lack of homogeneity of variances.

*Table 6. Fligner-Killeen and Levene's test of homogeneity of variances*

| Method | Statistical value | DF | p-value |
|---|---|---|---|
| Fligner-Killeen | 6.9158 | 2 | 0.0315 |
| Levene | 3.641 | 2 | 0.0355 |

When selecting the one-way ANOVA method with independent data, the following are considered: (a) Although there is a group with data with a lack of normal distribution, there is no evidence of extreme atypical data that would rule out the use of ANOVA, (b) Since the homoscedasticity of variances is not accepted, a heteroskedasticity ANOVA method (Welch test) is used that uses the Welch correction. Table 7 shows the results of the Welch test, using the oneway.test() function. Given that the p-value is greater than α, there is sufficient evidence to consider that at least two means have statistically significant differences.

*Table 7. One-way analysis of means*

| Method | F | Num DF | Num DF | p-value |
|---|---|---|---|---|
| Welch | 4.8148 | 2.00 | 25.038 | 0.01701 |

Finally, to compare the groups between pairs, the T test is applied with the Benjamini and Hochberg adjustment method, because it is one of the most powerful methods that exist to control the false discovery rate. The paired comparisons of distance between means are presented in Table 8, showing that there is a statistically significant difference only between the Industrial-Architecture groups (p-value < α). The industrial-medicine pair has a p-value close to the level of significance, but it is not enough to determine a significant difference.

*Table 8. Pairwise comparisons using T tests with non-pooled SD*

| p-value | Architecture | Industrial |
|---|---|---|
| **Industrial** | 0.040 | - |
| **Medicine** | 0.441 | 0.085 |

## 5. Discussion

The purpose of this research is to analyze IoT technology adoption among higher education students from different degrees through hands-on learning to determine the influence of higher education. The analysis of IoT technology acceptance has been applied to consumers [20], [32], professionals [30], educators [33], and students [34], even throughout literature review [31], but no work was found that compares multiple student groups to determine IoT acceptance.

One factor considered in the acceptance analysis is participant performance, where those with high averages are those who desire to adapt to new technologies [30].

In this case, in student performance, the degrees of Industrial and Architecture had similar mean, despite Industrial having some advantage due to its inherent prior knowledge. This implies there were no difficulties in executing the hands-on class, although Architecture students had no experience or related knowledge to facilitate the activities developed in class. Although the Medicine degree achieved lower performance, nearly half of the participants scored a 4 or higher. This was because the class was well-organized and provided students with all the necessary resources to develop applications without complications. Thus, not only were they qualified users for TAM application, but they also understood the application's functionality.

Regarding TAM-based of IoT acceptance results, it is evident that the Industrial degree embraced IoT technology better, despite lacking previous experience; their university education favors IoT acceptance. In contrast, literature presents a case where economics students had high acceptance of this technology [36], but they did not have a practical introduction to IoT. Returning to the research, in the Industrial degree, the highest scores were in PU, SI, and BI, where the first and third are related to IoT use in the future as professionals, while social influence is related to personal importance given to technology. In the Medicine degree, better acceptance was observed in PU and TCR, implying some validation of usability and confidence in the components used. In the Architecture degree, better acceptance was evidenced in PU and BI, implying a certain acceptance of technology usability with an interest in future use. However, this same degree had low acceptance scores in PE and PBC, indicating discomfort working with this technology [35]. Although these results denote a positive influence of the degree of study on IoT technology acceptance, statistical validation ensuring significant differences is required.

In statistical analysis, the Welch's ANOVA method for one-way independent data was used, not assuming equal variances, determining statistically significant differences in at least one pair of means. Pairwise comparison based on the T test confirmed significant difference only for Industrial and Architecture data with a p-value of 0.04. This finding indicates a relationship between higher education and IoT acceptance. Although a significant difference cannot be confirmed with the Medicine degree, as a significance of p-value=0.085 was obtained, very close to the established limit, this opens the opportunity to continue investigating this phenomenon in more university degrees.

An additional interesting finding is that the Architecture degree had worse IoT acceptance than Medicine despite surpassing it by almost 1 point in class performance.

This research provides an analysis of the influence of education on IoT acceptance, especially because the current literature does not present a similar study. On the other hand, regarding the limitations of this research, experiments with larger groups are required, gender balance in groups is also needed, and a greater number of groups could contribute to more conclusive results in the research. Additionally, hands-on learning can be complemented with prolonged use of developed applications through longitudinal studies that evaluate acceptance before and after use. These and other restrictions are challenges that can be addressed in future work.

## 6. Conclusion

This work presents an analysis of IoT acceptance among three groups of university student's degrees in Medicine, Industrial and Architecture, aiming to determine the influence of higher education through hand-on learning of this technology. The M5 Stack Core2 kit is used as hardware, along with UIFLOW programming software, while ThingSpeak configured with the MQTT protocol serves as the IoT platform. All these tools were chosen to facilitate hands-on learning and swiftly introduce students to IoT. To evaluate acceptance, a TAM validated in the IoT context is employed.

The obtained results are statistically analyzed using ANOVA and T-tests, determining statistically significant differences only for the Industrial-Architecture pair. It is concluded that higher education positively influences IoT acceptance. This suggests that technical degrees involving information technology content are more inclined toward IoT adoption. However, these findings are not conclusive, as statistical comparison with the Medicine degree did not confirm a significant difference. Finally, this work is limited by participant dimensions, both in size and the number of groups, thereby having new opportunities for future research.

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