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iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 15 No. 5 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijep.v15i5.55855

PAPER

Review of Introducing Augmented Reality and Internet of Things at Austrian HTL – Results from 2019 to 2024

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ABSTRACT

This paper gives an overview of the introduction of Augmented Reality (AR) and Internet of Things (IoT) technology at the Austrian higher technical vocational colleges (HTL). All areas, such as software implementation and organizational management for 42 locations, as well as server operation and training, are described. The necessary work and adjustments in the organizational area are also described. At the time of the introduction of the two completely new technologies, an educational concept for training and use in the HTL was also jointly developed and introduced in a working group. This paper describes an example of the introduction of one or more new technologies in engineering education, which can possibly be used as a best practice example for other areas.

KEYWORDS

Augmented Reality (AR), Internet of Things (IoT), engineering education, engineering pedagogy, introduction of new technologies, digitalization in engineering

1 INTRODUCTION

This paper describes the initial situation and the extent to which digital technologies from the field of Industry 4.0 [1] were used at Austrian higher technical vocational colleges (HTLs) before 2019.

1.1 Use of digital content at Austrian HTL before 2019

In 2017, common computer-aided engineering techniques such as computer-aided design (CAD) and finite element method (FEM) were used at Austrian technical colleges in the fields of mechanical engineering and mechatronics. Technologies and methods from the field of Industry 4.0 and digitalization were not used across the board at that time. Back in 2017, a group consisting of employees from the Austrian Ministry of Education and HTL professors were able to visit an initial demonstrator

Probst, A., Bernsteiner, R., Pachatz, W. (2025). Review of Introducing Augmented Reality and Internet of Things at Austrian HTL – Results from 2019 to 2024. *International Journal of Engineering Pedagogy (iJEP)*, 15(5), pp. 108–126. https://doi.org/10.3991/ijep.v15i5.55855

Article submitted 2025-02-07. Revision uploaded 2025-04-01. Final acceptance 2025-04-08.

together with PTC at the European 4.0 Transformation Center at RWTH Aachen University, known for their Industry 4.0 Maturity Index [2] and identify potential for its introduction at Austrian HTLs. Together with the Ministry of Education, it was decided to commission a pilot group with the introduction of AR and IoT at Austrian HTLs. The choice fell on the existing national working group ARGE 3D, which had already successfully introduced 3D CAD in Austrian HTLs in the fields of mechanical engineering, mechatronics, and industrial engineering. The aim was to leverage synergies by using existing resources and networks when introducing the new technologies. In addition, the Ministry of Education initiated the project "Digital product development" (DigiPro) [3] in 2019 and the following project "Professional digital methodologies and tools" (DigiPro-II) [4] in 2024 that defined the needed resources and responsibilities throughout Austria.

1.2 Objectives for the introduction of AR and IoT at the HTL

The following overarching goal was defined by the working group in consultation and coordination with the Austrian Ministry of Education: "Introduction of AR and IoT technology at 42 Austrian HTLs, various disciplines and locations."

In addition, the following sub-goals for the introduction were defined in detail by the Ministry of Education and the working group:

- Selection and procurement of suitable software for AR and IoT
- Selection of a central location for the operation of the necessary hardware
- Definition and procurement of the hardware required for operation
- Development of a multi-part training program by a pilot group
- Implementation of training courses at 40 Austrian technical colleges over a period of 2 school years
- Integration of digitalization content into HTL training
- Development of a didactic introduction to engineering pedagogy for AR and IoT
- Expertise in curriculum changes about the inclusion of new technologies
- Validation through accompanying surveys among staff and students

1.3 Related research questions

The following research questions are defined and examined as research questions for this paper as well as for the entire introduction:

RQ1: Does the introduction of AR and IoT create added value in HTL education?
RQ2: Do students and teachers have a generally positive attitude towards both technologies?
RQ3: What factors support the successful introduction of new technologies in teaching?
RQ4: What factors influence the fact that technical content is better understood using AR and IoT?

In order to answer the research questions, surveys have been conducted among students and teachers since the start of the training courses in 2019.

2 FRAMEWORK FOR THE USE OF AR AND IoT IN TEACHING AT THE HTL

This section describes the organizational structure and central management of the Austrian higher technical vocational colleges.

2.1 Ministry of Education and HTL in Austria

The subject-specific assignment of the Austrian HTL is currently anchored in the respective education directorate of the 9 individual federal states. The central curricula for all school types are drawn up by people from the school supervisory authority, such as directors and department heads, as well as professors with the relevant specialist expertise and practical experience in the industry. The Federal Ministry of Education coordinates and accompanies the process of developing the curricula and ensures that they are enacted into law. There are currently around 70 technical colleges in Austria [5], 42 of which are in the fields of mechanical engineering, mechatronics and industrial engineering. This paper looks at these 42 schools across Austria. There are 50.000 HTL students in total [5]. All HTLs in Austria are federal schools, whereas vocational schools are assigned to the respective federal states.

2.2 Virtualization of AR and IOT servers for Austrian HTL

An overview of the basic options for making IoT and AR services available to Austrian HTLs is provided. The concrete implementation of service hosting for DigiPro II is then presented.

Requirements for the operation of virtual AR and IoT servers. Internet of Things requires a server to receive all information and distribute it to other devices. AR also requires some services. Even if a single CAD design is to be visualized, a local service is required on the local computer. Vuforia Studio, for example, is split into a client application in the browser and a web server that runs on the local computer (http://localhost:3000).

When an AR application is to be published, the local web server sends the project to the Experience Service on the Internet. A stable server environment is therefore a basic requirement for the operation of IoT and AR. The overall application consists of several services that are closely connected and communicate with each other as well as with the clients. If this service is to be made available to many locations, even a very high-performance single server is no longer sufficient to provide adequate performance for all users.

Possible variants for the installation of virtual AR and IoT servers. Firstly, the possible options for installing the AR and IoT services will be examined.

Root server. Here, a "real" server with CPU, RAM, hard disks, power supply units, fans, etc. is used. The services are then installed on this root server.

Virtual server. The services are installed in exactly the same way as on the real server, but the underlying hardware is not real because a software layer intercepts all interactions of the services with the hardware with its own drivers and redirects them to another-real-hardware. Nevertheless, a full operating system is installed on this virtual machine.

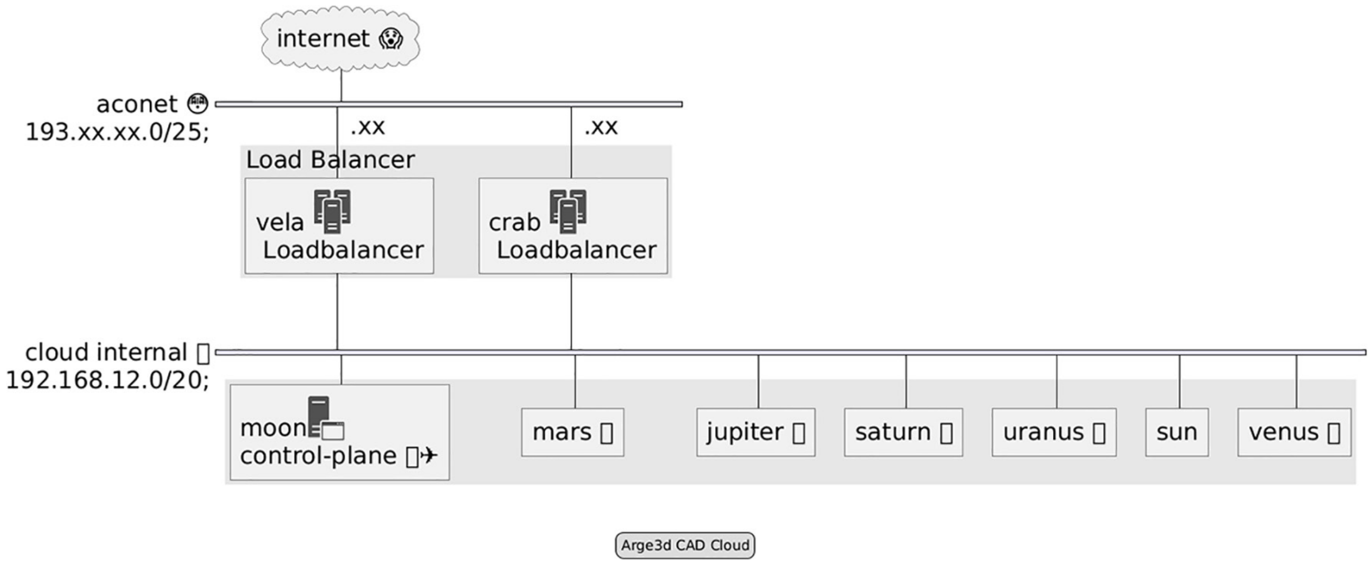

Fig. 1. DigiPro II network architecture

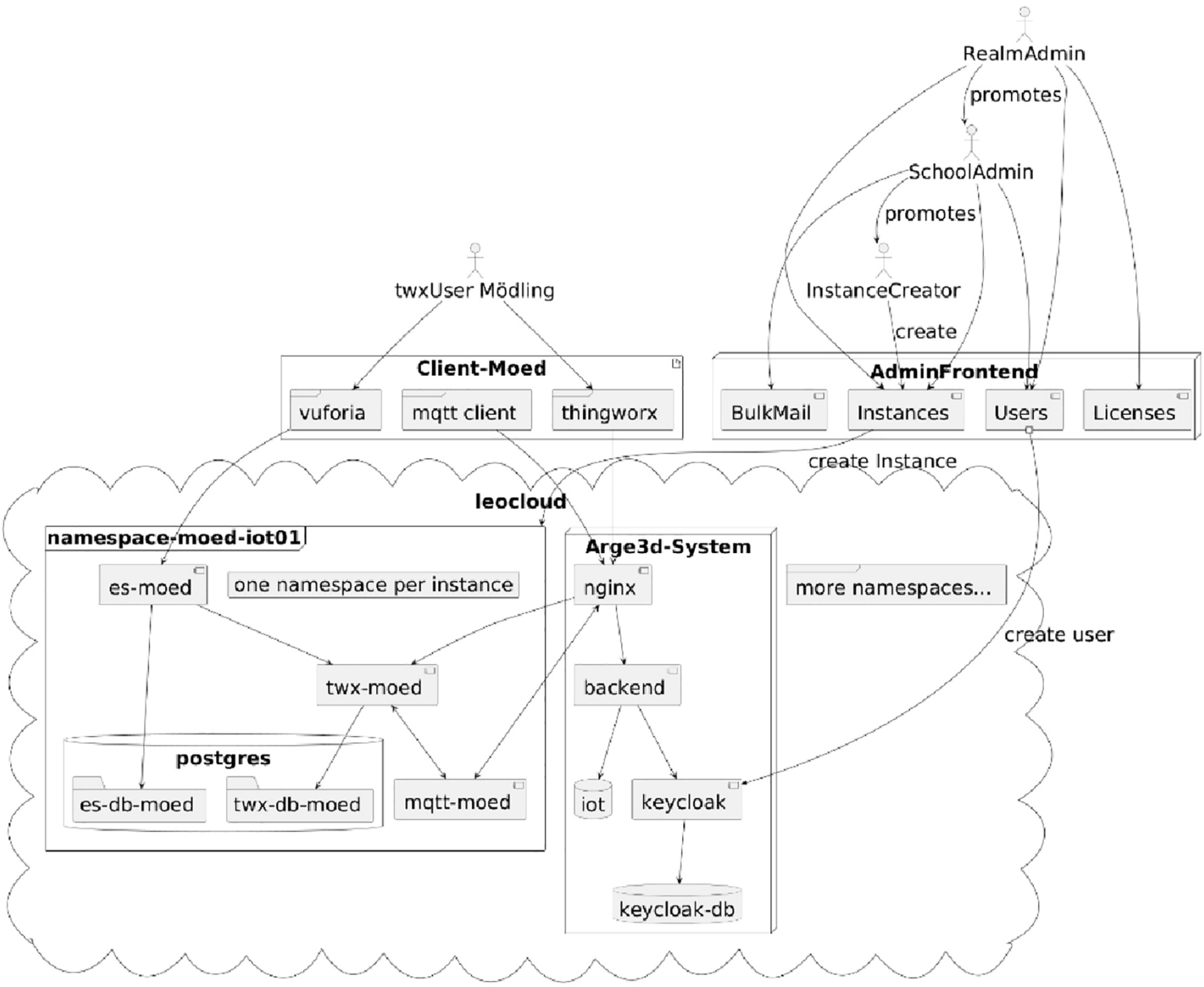

Fig. 2. DigiPro II deployment

Container with orchestration. Here, the overall application, which consists of several components that communicate with each other, is divided into so-called containers. Such a container provides a minimal operating system on which only a single service is installed. Correct interaction is ensured by an orchestration tool, e.g. docker compose.

Cloud computing with manual deployments. Cloud computing, in this case with Kuberbetes, is based on container technology. However, it removes the fixed binding of services to fixed hardware. The concept of pods is introduced, which in addition to the container, also contains information about how these containers are to be executed. Such pods can be moved between different servers automatically and transparently for the user. These servers do not even have to be located in the same data center. To install the services for a location, the administrator only needs to import a few so-called deployments together with their services, persistent volume claims and ingresses.

Cloud service for Austrian HTL. With currently 40 locations, the administration of such a cloud would also be very time-consuming. Therefore, in the DigiPro II Cloud, the task of the administrator who has to manage such deployments is performed by a separate, special cloud application, a "meta-deployment" so to speak. This additional cloud service stores the locations and their installations as well as authorized users in a database and provides a user interface that then performs an automatic installation and monitoring of all services for all locations (see Figures 1 and 2) such an installation is called an instance here.

Current implementation of the AR and IoT server. Implementation as a cloud service was chosen for DigiPro II. This means that requests for new instances are processed automatically. If hardware needs to be expanded or maintained, only existing computers need to be removed from the service (drain) or added (join). For the ThingWorx IoT solution used, the software supplier already provides Dockerfiles for creating containers.

For the Experience service, on the other hand, there is only an installation program, meaning that containerization must be performed independently.

3 INTRODUCTION OF AR AND IoT AT AUSTRIAN HTL

This chapter describes the piloting, planning and implementation of the training courses for the two technologies at the Austrian higher technical vocational colleges.

3.1 First steps in AR and IoT at Austrian HTL

In order to determine the potential and possibilities of the two technologies, a pilot group was initially set up under the leadership of the Austrian Ministry of Education. The aim was to explore the technology in an industrial environment and in a university environment together with the selected software manufacturer and, if possible, to discuss the possibilities for use in Austria with the engineers on site. In 2019, a study trip was made to the digital transformation center at RWTH Aachen University, which is operated by PTC together with RWTH Aachen University. Here, a team of Austrian HTL professors were able to examine the technologies in use, identify possible application scenarios and draw up an initial rough plan for the coming years.

A group of HTL engineers from all over Austria was selected very quickly in order to get as wide a spectrum as possible across the various disciplines and regions. A two-day training course was then arranged with the software manufacturer PTC at the HTL Linz Litec. Now that the engineers knew what the technology was capable of, the focus remained on training the engineers in how to use the technology. It was already clear in advance that hardware in the form of Raspberry Pi or Arduino was required for the IoT-training, which all participants had to bring to the training. In order to create an application scenario that was as realistic as possible, it was decided to test the two technologies on a real industrial assembly. A gearbox was selected, which was then modified accordingly. Sensors were placed on the gearbox, which could read out the speed. In addition, the entire gearbox was modeled in 3D CAD to enable its use in Augmented Reality.

3.2 Hardware for training courses

For the initial phase, the pilot group selected Raspberry and Arduino as the hardware platform for the training courses. In addition to good availability, both products offer scalability and expandability. In addition, there are communities for Raspberry and Arduino whose knowledge can be queried. For the Raspberry in particular, the focus was on low-threshold access, as the pilot group and the first training groups included people with little programming experience.

Nevertheless, both Arduino and Raspberry had to be configured for the use in training courses. In addition to a hardware specification, which the training participants had to bring with them, this also included adapting the software for operation. In particular, the data exchange from the PC to Raspberry and Arduino was a challenge for the participants at the beginning. The advantage of an identical hardware specification for all participants was and is the reduced effort involved in the training courses. No adaptations need to be made on site during training if participants use different hardware. The time saved by adopting the hardware leaves more time for training and discussions.

Over time, additional alternatives to the hardware mentioned above have emerged. One example is the ESP32 [6] and its hardware derivatives, which, in addition to their extended functionalities, also have the advantage of requiring less space. Nevertheless, the two products Raspberry and Arduino were and are still used as the standard for training courses and training materials for all professors and students.

The option of using the students' own smartphones was developed specifically for data acquisition and for controlling the models in Augmented Reality.

The Phyphox app from RWTH Aachen [7] already shows impressively which sensor data can be accessed on the smartphone. All this sensor data can be used as a data source for the platforms. This is particularly advantageous in laboratory operation, as it eliminates the need for time-consuming preparatory work, leaving only the connection between the smartphone and the IoT platform to be established. The smartphone is particularly suitable for controlling the AR models, as it is available everywhere and the students usually have suitable, new devices.

Smartphones can also be used as a data source in a real scenario. One example of this is the Zero Emission Challenge of the Austrian HTLs, a competition that is based on the Formula Student regulations. Here, both the route and the speed profile of the participating vehicles are recorded, documented, and evaluated on the basis of the drivers' smartphones. This eliminates the need to install complex sensor technology in vehicles.

In addition, the various HTL locations purchased the Microsoft HoloLens [8] and HoloLens2 products for training and laboratory operations. This made it possible to hold our own HoloLens training course with around 20 participants in 2019. HoloLens is currently the high-end hardware for AR technology. Due to the lack of further development by Microsoft and the lack of equivalent quality alternatives, the devices are still used at higher technical vocational colleges. Figure 3 shows the interaction between IoT and AR devices and software in the current HTL configuration.

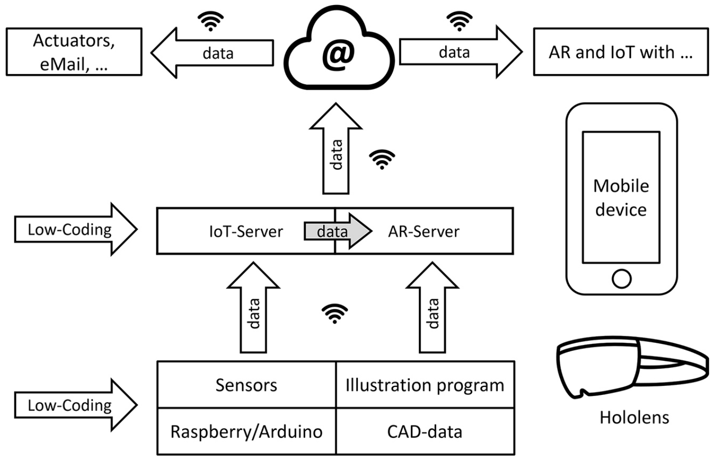

Fig. 3. Interaction of AR and IoT from data generation to transfer to end devices

3.3 Creation of a pedagogical concept for teaching AR and IoT

The working group was commissioned by the Austrian Ministry of Education to develop a pedagogical concept for the training of engineers and for use in teaching at Austrian technical colleges. It quickly became clear that pure software training would not meet the requirements for teaching at the HTL. The working group therefore developed a pedagogical concept that in addition to the HTL requirements, also takes into account the needs of industry and SMEs.

The definition of the target group was and is also important. Initially, the focus was only on design engineers, but based on the pilot group's experience, it quickly became clear that the target group included all engineers from the fields of mechanical engineering, mechatronics and industrial engineering. One example of this is the strong networking of the control systems with the IoT platforms, which meant that colleagues from this area were and are also interested in the training. A possible expansion to other target groups such as electrical engineering, civil engineering and chemistry was postponed to a later date as the focus had to be placed on a limited number of training participants for resource reasons and due to the coronavirus pandemic.

3.4 Training series for AR and IoT at HTL

During the pilot and the initial discussions, it became clear that the introduction of the two technologies, AR and IoT, could not be dealt with in a single training course. The reason for this was the novelty of the two technologies and the rapid development in the technical field. In addition, it was not yet clear in the pilot phase what options would be available in terms of hardware (integration of hardware such as

Raspberry or PLC hardware). There was also uncertainty regarding the training participants; the initial focus was on professors from the field of construction, due to AR technology. However, it quickly became clear that a completely different target group needed to be involved for the IoT area. Professors from the field of control and regulation technology were identified as the target group. This meant that many technicians involved in the product development of industrial products and systems could be included in the training. In terms of comprehensive training, it was determined that both target groups would be trained in both AR and IoT. In addition to the broader use of both technologies, this also had the advantage that the training concepts and content could be simplified and standardized. Based on a joint assessment and coordination, it was decided that 3 periods would be required for each training cycle.

As it was not possible to train colleagues from 42 locations in one training cycle, it was decided that one colleague from each of the 42 HTLs would take part in the first training cycle. In addition, the first training cycle was restricted to participants from the fields of mechanical engineering and mechatronics. This involved the effort of selecting standardized hardware (see section 3.2) sand procuring it by the respective locations themselves. A lot of persuasion was required here, as the professors from the locations naturally wanted to take the existing hardware with them to the training. To ensure that the training ran as smoothly as possible, it was made clear through collegial communication that only standardized hardware would be accepted for training. The participants also had to install the required software for AR and IoT on their PCs or laptops in advance. From experience with other training courses, the installation of software on the PC is a significant negative time factor for the training participants. The required software was provided centrally in advance and in good time as a download, installation instructions were written and sent to the training participants. The second training cycle was then also evaluated for participants from the field of industrial engineering. Unfortunately, both the trainers and the course participants were challenged with the problems and challenges of the Corona pandemic. It was therefore only possible to carry out the second training cycle with the greatest effort and compliance with all safety requirements (masks, distance, etc.). The third training cycle covered all those people from the mechanical engineering, mechatronics, and industrial engineering departments who had not yet received training or were willing to do so again. Here it was possible to draw on the experience of the previous training courses. In consultation with the Ministry of Education, it was then decided to extend the target group to include the IT and electrical engineering departments. Here, too, an entire training cycle has been carried out so far; the specialist area of construction technology is still open at the beginning of 2025. Training courses are already being prepared for this specialist area.

3.5 Platform for regular knowledge exchange between professors

In addition to the training courses, the HTL professors requested a regular exchange on the topic of digitalization, in particular on AR and IoT. A group of experts also agreed on the format and content of such a training format. A two-day workshop was agreed upon as the format, which does not replace the training courses but shows the current state of the technology by the manufacturers of AR and IoT software. In addition, key players and companies from the field of digitalization will be invited to demonstrate the application of the technologies in industrial practice using concrete examples. This workshop was held for the first time in December 2024 with many participants, and the feedback from both participants and external companies was extremely positive. The consensus was that this format should definitely be retained and offered as a regular, annual training course for HTL professors. All these training measures were and are only possible thanks to the consistently great support of the Ministry of Education and the teacher training colleges responsible, which act as organizers of the training courses.

4 ACCOMPANYING SURVEYS 2019 TO 2024

4.1 Methodology and design of the study

Augmented Reality and IoT are used to help to understand technical content better. Consequently, it is highly relevant to identify the factors that influence this better understanding, which is the aim of this research.

Data collection. A questionnaire was used to collect empirical data. Table 1 shows the questions relevant for this analysis. The same questions were asked for IoT and AR. All items had to be rated on a Likert scale from 1 (“I totally agree”) to 5 (“I totally disagree”). A detailed description of the questionnaire design and the data collection phase can be found in [9] and [10].

Table 1. Questions for students for IoT and AR

Variable	Question	Feature/Target
IoT/AR_understanding	I think AR helps understand technical concepts	Target
IoT/AR_enjoy	I enjoy using (learning/teaching) AR	Feature
IoT/AR_interesting	I am personally interested in AR	Feature
IoT/AR_important	I think AR will be important in the future	Feature
IoT/AR_attractive	I think AR makes technical education more attractive	Feature

Features are the input data or independent variables that capture different characteristics of the subject being analyzed. Targets, on the other hand, are the output or dependent variables that the model seeks to predict or classify using the features provided.

Descriptive statistics of variables. Table 2 presents the IoT-results from the students’ perspective along with a detailed analysis of the results [9, 10]:

Table 2. Responses IoT and AR – students

	Frequency	Mean IoT	Std. Dev. IoT	Mean AR	Std. Dev. AR
IoT/AR enjoy	170	2.34	1.014	1.92	1.068
IoT/AR interesting	170	2.46	1.126	2.22	1.074
IoT/AR important	171	1.77	1.046	1.87	1.054
IoT/AR understanding	170	2.28	1.077	2.01	1.096
IoT/AR attractive	171	2.23	1.046	1.98	1.046

All mean values are below 2.5 (where 1 represents “I totally agree” and 5 represents “I totally disagree”), suggesting a generally positive attitude toward IoT and AR.

The teachers’ answers are presented in the following Table 3. An in-depth analysis of the teachers can be found in [11] and [12].

Table 3. Responses IoT and AR – teachers

	Frequency	Mean IoT	Std. Dev. IoT	Mean AR	Std. Dev. AR
IoT/AR enjoy	44	1.80	1.069	1.75	1.102
IoT/AR interesting	45	1.62	0.886	1.64	0.908
IoT/AR important	45	1.52	0.927	1.51	0.869
IoT/AR understanding	44	2.20	1.002	1.93	0.998
IoT/AR attractive	45	1.71	1.036	1.51	0.895

All mean values are below 2.0, except for IoT_understanding with a mean of 2.2, using the same scale as in Table 2. Again, this represents a very positive attitude concerning IoT and AR.

4.2 Machine learning-based classification

Based on the questions, various machine learning (ML) algorithms were trained and evaluated to identify the best algorithm for this application. Each model is trained and tested with the same input features to ensure comparability. Since the data are ordinal, classification algorithms are used. A supervised learning approach was applied.

Classification models. In this section, the used algorithms are described [13–16]:

- **Random Forest:** An ensemble learning method that constructs multiple decision trees during training and combines their outputs to enhance accuracy and reduce overfitting. It is robust, effectively handles missing data, and lowers variance compared to a single decision tree.
- **Logistic Regression:** A classification algorithm used to estimate the probability of a binary outcome. It can also be extended to handle multi-class classification problems.
- **Support Vector Machine (SVM):** A powerful classification algorithm that determines the optimal hyperplane for separating data points into distinct classes. It performs well in high-dimensional spaces.
- **Decision Tree:** A tree-based algorithm where nodes represent features, branches correspond to decision rules, and leaves signify outcomes. While intuitive and easy to interpret, it is prone to overfitting and sensitive to small variations in data.
- **Naive Bayes:** A probabilistic classification algorithm based on Bayes' theorem, which calculates the conditional probability of a class given specific features. It assumes feature independence, though it can still capture essential relationships between features and target classes, making it effective in many real-world applications.
- **k-Nearest Neighbors (kNN):** A non-parametric, supervised learning classifier that makes predictions based on the proximity of data points. In classification tasks, it assigns a class label based on a majority vote of the nearest neighbors.
- **AdaBoost:** An ensemble learning method that combines multiple weak learners, typically decision trees with a single split, to form a strong classifier. It assigns higher weights to misclassified samples and retrains weak learners iteratively, aggregating their predictions through weighted voting.
- **Neural Network (NN):** An (artificial) Neural Network is a computational model inspired by the structure and function of the human brain. It consists of layers of artificial neurons (nodes) that process and learn patterns from data. An NN

consists of three layer types: a) Input Layer that receives raw data (e.g., images, text, numbers), b) Hidden Layers that perform computations and extract features using weighted connections, and c) Output Layer that produces the final prediction or classification.

Model metrics. The following metrics with their significance are used to evaluate machine-learning algorithms [17, 18]:

- **AUC (Area Under the Curve):** Measures the model's ability to distinguish between classes. The higher the value, the better. AUC is a key metric in classification tasks, as it indicates how well the model distinguishes between classes. AUC is well-suited for imbalanced datasets.
- **CA (Classification Accuracy):** The proportion of correctly classified instances. A higher score indicates better overall classification performance. CA measures the overall correctness of the model and is used for balanced datasets.
- **F1:** Harmonic mean of precision and recall, balancing both metrics. Higher values indicate a better balance.
- **Prec (Precision):** Measures how many predicted positives are actually positive. High precision reduces false positives.
- **Recall:** Measures how many actual positives were correctly classified. High recall reduces false negatives.
- **MCC (Matthews Correlation Coefficient):** MCC is a balanced metric that considers true or false positives and negatives. MCC is a robust metric that accounts for class imbalance. Values close to 1 indicate strong predictions.
- **Spec (Specificity):** Measures the ability to correctly identify negatives. A higher score indicates fewer false positives.
- **LogLoss (Logarithmic Loss):** Measures how confident the model is in its predictions. Lower values indicate better probabilistic predictions.

4.3 Model scores – Internet of Things

Table 4 presents multiple performance metrics for the machine learning models used.

Table 4. Model scores – IoT

Model	AUC	CA	F1	Prec	Recall	MCC	Spec	LogLoss
Random Forest	0.711	0.406	0.402	0.408	0.406	0.171	0.761	1.714
Logistic Regression	0.719	0.471	0.466	0.476	0.471	0.260	0.783	1.146
SVM	0.693	0.394	0.378	0.368	0.394	0.145	0.749	1.249
Tree	0.623	0.312	0.308	0.318	0.312	0.056	0.734	9.371
Naive Bayes	0.731	0.506	0.505	0.517	0.506	0.327	0.810	1.243
kNN	0.706	0.447	0.437	0.444	0.447	0.227	0.775	3.713
AdaBoost	0.659	0.335	0.335	0.342	0.335	0.083	0.737	6.499

The best overall model is Naïve Bayes. It has the highest AUC (0.731) and Classification Accuracy (CA) of 0.506, suggesting it performs best in distinguishing between classes. It also has the best F1-score (0.505) and Recall (0.506), making it the most balanced model. MCC (0.327) is also the highest, indicating good correlation with actual outcomes.

Logistic Regression performs slightly worse than Naïve Bayes but still has a good AUC (0.719), CA (0.471), and a relatively low LogLoss (1.146), meaning it provides reliable probability estimates. Random Forest also performs reasonably well with AUC (0.711) and moderate scores across metrics.

A lower LogLoss means better probabilistic predictions. Logistic Regression (1.146) and Random Forest (1.714) are among the best. Decision Tree (9.371) and AdaBoost (6.499) have very high LogLoss, meaning their probability estimates are unreliable.

Naïve Bayes is the best choice for this dataset based on its balance of performance metrics, Logistic Regression is a strong alternative.

Neural network – IoT. In addition, an NN was trained with the same data. The NN is evaluated with different model parameters. Table 5 depicts the finally used parameters [19, 20]:

Table 5. Neuronal model parameters used for both, IoT and AR

Parameter	Value	Description
Hidden layers	100	Number of layers of neurons that is neither the input nor the output layer.
Activation	tanh	The hyperbolic tangent (Tanh) function is an activation function that converts a node's input signal in a neural network into an output signal, which is then transmitted to the next layer.
Solver	SGD	Stochastic Gradient Descent (SGD) is an iterative optimization technique used to refine an objective function, provided it has appropriate smoothness characteristics.
Alpha	0	Alpha is a regularization parameter that helps prevent overfitting by limiting the magnitude of the weights.
Max iterations	200	One iteration is a single gradient update (update of the model's weights) during training.
Replicable training	YES	Defines if the models' training should be reproducible or not. Reproducibility is an important aspect.

Table 6 shows the results of the NN compared to Naive Bayes.

Table 6. Model scores Neural Network and Naive Bayes – IoT

Model	AUC	CA	F1	Prec	Recall	MCC	Spec	LogLoss
Naive Bayes	0.731	0.506	0.505	0.517	0.506	0.327	0.810	1.243
Neural Network	0.714	0.441	0.438	0.443	0.441	0.224	0.780	1.262

The results show that Naive Bayes performs better than the NN. The following feature importance analysis is based on Naive Bayes.

Neural Network – IoT. Feature importance quantifies the impact of each feature on a model's predictions by assessing the increase in prediction error when the feature's values are randomly shuffled, disrupting its relationship with the target variable. A higher importance score indicates that the feature has a greater influence on the model's predictions.

In this analysis, permutation-based feature importance is used, which measures the reduction in a model's performance score when a single feature's values are randomly permuted. This process breaks the feature-target relationship, and the resulting drop in the model's score reflects the extent to which the model relies on that feature [21, 22].

Different metrics result in different features of importance results. The feature of importance is presented since it is well suited for imbalanced data sets.

Table 7 presents four IoT-related features along with their mean importance scores and the standard deviation (Std) of these scores, which likely reflect the average contribution of each feature to the model's predictions across multiple runs.

Table 7. Feature Importance based on Naive Bayes-AUC – IoT

Rank	Feature	Mean	Std. Deviation
1	IoT_attractive	0.043	0.016
2	IoT_enjoy	0.038	0.006
3	IoT_interesting	0.019	0.012
4	IoT_important	0.016	0.008

The most significant feature is IoT_attractive, with a mean importance score of 0.043 and a standard deviation of 0.016, suggesting that this factor has the greatest impact on the model's predictions while exhibiting some variability. Ranked second is IoT_enjoy, with a mean importance of 0.038 and a lower standard deviation of 0.006, indicating that it is also a crucial factor but with more consistency in its contribution. IoT_interesting follows in third place, with a mean importance of 0.019 and a standard deviation of 0.012, showing a noticeable drop in influence compared to the top two features. Finally, IoT_important ranks fourth with the lowest mean importance.

4.4 Model Scores – Augmented Reality

Table 8 presents multiple performance metrics for the machine learning models used. A description of the models and scores can be found in sections 4.2.1 and 4.2.2.

Table 8. Model Scores – IoT

Model	AUC	CA	F1	Prec	Recall	MCC	Spec	LogLoss
Random Forest	0.748	0.518	0.512	0.517	0.518	0.296	0.771	1.443
Logistic Regression	0.765	0.512	0.509	0.513	0.512	0.287	0.768	1.027
SVM	0.752	0.518	0.498	0.480	0.518	0.291	0.782	1.040
Tree	0.700	0.494	0.491	0.492	0.494	0.265	0.775	8.030
Naive Bayes	0.773	0.529	0.522	0.523	0.529	0.325	0.790	1.042
kNN	0.745	0.529	0.509	0.514	0.529	0.305	0.759	5.855
AdaBoost	0.711	0.547	0.544	0.545	0.547	0.344	0.791	5.670

The best overall model is Naïve Bayes with the highest AUC (0.773), a strong F1 (0.522), and a good balance between precision, recall, and specificity. The highest Accuracy and F1 Score has AdaBoost (0.547 accuracy, 0.544 F1 score) which makes it the best at correct classification and balanced performance. Logistic Regression provides the most confident predictions (Lowest LogLoss: 1.027), meaning it makes the most certain probability estimates. The best at identifying negatives are SVM (0.782) and AdaBoost (0.791) which have high specificity, meaning they correctly classify negative instances. For overall balanced performance, Naïve Bayes is the best choice.

Neural Network – AR. In addition, an NN was trained with the same data. The NN is evaluated with different model parameters. The same parameters were used for AR as for IoT. Table 9 shows the results of the NN compared to Naive Bayes.

Table 9. Model scores NN and Naive Bayes – AR

Model	AUC	CA	F1	Prec	Recall	MCC	Spec	LogLoss
Naive Bayes	0.773	0.529	0.522	0.523	0.529	0.325	0.790	1.042
Neural Network	0.758	0.500	0.492	0.490	0.500	0.272	0.773	1.104

The metrics show that Naive Bayes and the NN for AR are similar. The following feature importance analysis is based on Naive Bayes.

Feature Importance – AR. Table 10 depicts the importance scores of the four features. Again, the importance score reflects the decrease in a model score when a single feature value is randomly shuffled.

Table 10. Feature Importance based on Naive Bayes-AUC – AR

Rank	Feature	Mean	Std. Deviation
1	AR_important	0.057	0.014
2	AR_attractive	0.050	0.014
3	AR_enjoy	0.027	0.009
4	AR_interesting	0.001	0.014

The most influential feature is AR_important, with a mean importance of 0.057 and a standard deviation of 0.014, indicating that this feature has the strongest impact on the model while also displaying some variability. The second most important feature is AR_attractive, with a mean importance of 0.050 and a slightly lower standard deviation of 0.014, suggesting that it also plays a significant role in the model's decisions but with slightly less variation.

The feature AR_enjoy ranks third. While it is less influential than the first two features, it still contributes meaningfully to the model. Finally, AR_interesting has the lowest importance. The extremely low mean suggests that this feature has a negligible impact on the model, though its relatively high standard deviation indicates occasional fluctuations in its importance across different model evaluations. This analysis shows that AR_attractive has hardly any impact on helping to understand technical content easier.

Since the trained NN leads to similar results compared to Naive Bayes, the feature analysis is also carried out with the results of the NN. Table 11 shows the related results.

Table 11. Feature Importance based on NN-AUC – AR

Rank	Feature	Mean	Std. Deviation
1	AR_important	0.087	0.016
2	AR_attractive	0.067	0.014
3	AR_enjoy	0.057	0.013
4	AR_interesting	0.023	0.009

The most important feature is AR_important, with a mean importance score of 0.087 and a standard deviation of 0.016, indicating that this feature has the highest contribution to the model's decisions while maintaining a relatively low variability. Following this, AR_attractive ranks second, with a mean importance of 0.067 and a standard deviation of 0.014, suggesting that it is also a key factor but slightly less influential than AR_important.

In third place, AR_enjoy has a mean importance score of 0.057 and a standard deviation of 0.013, showing a further decrease in influence. Finally, AR_interesting is ranked fourth with a mean importance of 0.023 and a standard deviation of 0.009, indicating that while it still plays a role, it has a significantly lower impact on the model's outcomes compared to the other features.

5 ADVANCES IN THE INTRODUCTION OF AR AND IoT FROM 2019 TO 2024

5.1 Position in the HTL curriculum 2019

In 2019, the curricula of the various subject areas at Austrian technical colleges contained little digital content. Therefore, in addition to the planned introduction of AR and IoT technologies, various committees under the leadership of the Austrian Ministry of Education worked on anchoring digital content in general and AR and IoT in particular in the curricula. As these curricula are drawn up in generations and prescribed by law, it is only possible to introduce new content in the curriculum revision cycle. This was done with the involvement of the school administrators concerned, the working group, and the Ministry of Education. An example of this is the curriculum for industrial engineering, which also documents the progress of the curricula. It should be noted that in Austria these curricula do not represent a framework curriculum in which teachers teach those parts that they consider important. On the contrary, the content of the curricula must be implemented by the teachers at the locations. Ensuring implementation is the responsibility of the school supervisory board, in this case the department heads and directors of the respective HTL locations.

5.2 Position in the HTL curriculum 2024

In 2024, there are several prescribed and valid curricula that include AR and IoT as components. They also include other content relating to digitalization technologies and Industry 4.0. Due to the heterogeneity of the HTL curricula, AR and IoT content is anchored in different subjects. There is therefore no separate subject that explicitly covers the content of the two technologies. This means that students who are taught according to these curricula know and can use these technologies. Feedback from the business community is very positive about these developments.

5.3 Quality assurance – creating a category at the nationwide YAEC competition

To provide a possible showcase for the new digital content, it was decided together with the Austrian Ministry of Education to introduce a separate category "Digitalization" in the Young Austrian Engineers Contest (YAEC) and to invite the various locations to submit their work in this category. The YAEC is a joint competition between the Austrian Ministry of Education, all HTLs, and various software manufacturers to show the level of Austrian students. It is a form of talent promotion that is followed with great interest by the Ministry of Education and the industry. A separate paper with detailed information on this competition will be published soon at the upcoming ICL conference in Budapest in October 2025.

Due to the differences between the AR and IoT submissions, a separate evaluation scheme was created where necessary, as the existing evaluation scheme for the mechanical engineering design and development student work could not be applied. Naturally, the number of submissions for AR and IoT since 2023 has been relatively low, as the technology is very new for both teachers and students. In contrast to the mechanical engineering design work, which has been carried out on the various CAD programs for almost 25 years, AR and IoT technology are relatively new at the Austrian HTL. However, an increasing number of submissions can be observed from year to year.

6 CONCLUSION

6.1 Answering the research questions

RQ1: Does the introduction of AR and IoT create added value in HTL education?

All means in Table 2 (IoT) and Table 3 (AR) are below a value of 2.5, which can be interpretated as a positive indicator of the technologies value from the students' perspective. Additionally, there is positive feedback from industry and SME companies concerning the students' knowledge of AR and IoT technologies.

RQ2: Do students and teachers have a generally positive attitude towards both technologies?

The findings suggest that both groups generally hold a highly positive view of IoT education, though teachers' perceptions are slightly more favorable than those of students. Responses were assessed using a Likert scale, where lower mean scores signified stronger agreement. Similarly, both groups also expressed a very positive perception of AR education, with teachers viewing it somewhat more favorably than students. Overall, these results indicate that IoT and AR education at HTLs can be regarded as successful.

RQ3: What factors support the successful introduction of new technologies in teaching?

- Above all, it is important to have a functioning system environment in terms of hardware and software in which the AR and IoT tools are made available.
- The resources needed are provided by the Ministry of Education.
- The development team is supported by the Ministry of Education.
- Use of tools (Thingworx and Vuforia) that are also used in industry.
- Support from the manufacturers of the AR and IoT tools.
- An existing nationwide working group was commissioned with the introduction.
- Development of a targeted didactic training concept for students and teachers.

- Development and provisioning of best practice examples that can be used by all teachers and students in the classroom.
- Regular annual exchange of teachers on the specialist topics of AR and IoT and digitalization, with presentations from well-known companies in this field.

RQ4: What factors influence the fact that technical content is better understood using AR and IoT?

Among the IoT-related features, IoT_attractive is the most influential, having the highest mean importance score, though it shows some variability. IoT_enjoy ranks second, slightly less impactful but more consistent in its contribution. IoT_interesting comes third, with a significant drop in influence compared to the top two features and a moderate level of variability. Lastly, IoT_important has the lowest mean importance, making it the least impactful IoT-related feature in the model.

For AR-related features, AR_important ranks as the most significant, contributing the most to the model's predictions while maintaining relatively low variability. AR_attractive follows as the second most influential feature, with a slightly lower impact but still playing a crucial role. AR_enjoy is in third place, showing a further reduction in importance compared to the top two. Lastly, AR_interesting has the lowest mean importance among AR-related features, indicating that while it still plays a role, it has a considerably smaller impact on the model's decisions than the other features.

6.2 Summary and outlook

This paper describes the successful introduction of the two technologies AR and IoT at Austrian higher vocational technical colleges in the years 2019 to 2024. The two technologies, which had not been used at all until then, were introduced nationwide at higher technical colleges for mechanical engineering, mechatronics, and industrial engineering. Teachers who were trained in both technologies came particularly from the areas of mechanical engineering design, product development, and control engineering. In addition to the training courses, best practice examples and exercises were also developed as part of a holistic educational concept and made available to both groups, the teachers and students. Surveys were also conducted among teachers and students during this period, which showed that both groups recognize the added value and are in favor of using the technology in teaching. For the future, the introduction of AR and IoT in the specialist areas of construction technology and IT is planned and, in some cases, already being implemented. In technical terms, further development is planned regarding the use of AI and the use in connected mechatronic systems – known as "digital twin". As a quality assurance measure, the creation of a separate "Digitalization" category in the Young Austrian Engineers Contest (YAEC) has already taken place, and increasing the number of submissions on the two technologies is on the agenda. Overall, the use of the two technologies AR and IoT is making a positive contribution as components of the Austrian Ministry of Education's digitalization initiative.

7 ACKNOWLEDGMENTS

The projects DigiPro and DigiPro-II discussed in this paper have been authorized by the Austrian Federal Ministry of Education, Science and Research.

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