Graphical Abstract

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Highlights

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IoT System for Detecting Distractions in Children During Academic Activities at Home★

Gleistoon Guerrero-Ulloa[a,b,**,1], Carlos Almeida-Dueñas[a,*], John Plazarte-Suárez[a], Orlanzo Erazo-Moreta[a], Miguel J. Hornos[b] and Carlos Rodríguez-Domínguez[b]

[a]Faculty of Engineering Sciences, State Technical University of Quevedo, Central Campus, Quito Avenue km. 1 1/2, on the way to Santo Domingo de los Tsáchilas, Quevedo, 120301, Los Ríos, Ecuador

[b]Software Engineering Department, University of Granada, Calle Periodista Daniel Saucedo Aranda s/n, 18071 Granada, Spain

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ABSTRACT

Torddis, an innovative system developed to address the impact of parental absenteeism on academic performance, utilises Artificial Intelligence (AI) and Internet of Thongs (IoT) technologies to monitor students' distractions in real-time within their homes, identifying facial expressions of distraction, unauthorised objects, and signs of drowsiness. This technological solution, crafted following the TDDM4IoTS methodology, integrates a mobile application and an IoT device, providing tutors with an accessible and efficient tool for academic supervision of their students. The system's usability was positively evaluated by tutors, achieving a notable 81.46% on the SUS (System Usability Scale: see Appendix C), emphasising its benefits for enhancing students' concentration and providing informative support to parents. Although its efficacy was acknowledged, improvements in camera quality were recommended. Torddis promises a significant impact on education, aiming to be a strong ally in learning and presenting opportunities for further development.

1. Introduction

Over the past decade, fast-paced lifestyles and increasing workloads have led to a rise in parental absenteeism during the hours reserved for primary school students' activities. This absence and lack of support have been shown to directly affect young students' academic performance. Teachers have noted a decline in performance and discipline metrics, potentially negatively impacting students' self-esteem and other psychosocial aspects. Moreover, the literature suggests that emotional support at home is an essential pillar for children to focus on their studies (Seidu, Arthur-Holmes, Agbaglo and Ahinkorah, 2022).

Emotional interference not only affects educational success but also permeates all aspects of students' lives (Sabina Åke and Antonsson, 2023). A family environment that fosters positive communication and genuine interaction can lead to significant improvements in students' wellbeing and social skills (Raúl Navarro and Víllora, 2024). Given this scenario, technological tools that utilise Artificial Intelligence (AI) and Internet of Thongs (IoT) have the potential to monitor and measure children's distractions, providing crucial data for decision making focused on improving attention and learning (Alvear-Puertas, Rosero-Montalvo, Peluffo-Ordóñez and Pijal-Rojas, 2017; Berrezueta-Guzman, Pau, Martín-Ruiz and Máximo-Bocanegra, 2021).

★ Torddis is an innovative IoT system designed to monitor and improve student concentration at home, providing tutors with tools to detect distractions and maintain focus on school tasks.

*Corresponding author

**Principal corresponding author

gguerrero@uteq.edu.ec (G. Guerrero-Ulloa); carlos.almeida2017@uteq.edu.ec (C. Almeida-Dueñas); john.plazarte2017@uteq.edu.ec (J. Plazarte-Suárez); oerazo@uteq.edu.ec (O. Erazo-Moreta); mhornos@ugr.es (M.J. Hornos); carlosrodriguez@ugr.es (C. Rodríguez-Domínguez)

https://www.uteq.edu.ec (G. Guerrero-Ulloa); https://www.uteq.edu.ec (C. Almeida-Dueñas); https://www.uteq.edu.ec (J. Plazarte-Suárez); https://www.uteq.edu.ec (O. Erazo-Moreta); https://lsi.ugr.es/informacion/directorio-personal/miguel-juan-hornos-barranco (M.J. Hornos); https://lsi.ugr.es/informacion/directorio-personal/carlos-rodriguez-dominguez (C. Rodríguez-Domínguez)

ORCID(s): 000-0001-5990-2357 (G. Guerrero-Ulloa); 0000-0002-0959-922X (C. Almeida-Dueñas); 0000-0001-5488-9982 (J. Plazarte-Suárez); 0000-0001-5642-9920 (O. Erazo-Moreta); 0000-0001-5722-9816 (M.J. Hornos); 0000-0001-5626-3115 (C. Rodríguez-Domínguez)

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Student concentration is a factor that can determine their capacity to learn and apply the knowledge imparted by teachers. In a study conducted by Terraza Arciniegas, Amaya, Piedrahita Carvajal, Rodriguez-Marin, Duque-Muñoz and Martinez-Vargas (2022), a system is proposed to monitor student attention in an online learning environment, based on computer vision algorithms. The authors use a Recurrent Neural Network (RNN) to identify facial landmarks, which detects if a student is maintaining a frontal position towards the device used to attend an online class. Their study highlights some of the limitations present in current proposals.

Conversely, the work by Berrezueta-Guzman et al. (2021) presents a robotic system designed to interact with children diagnosed with Attention Deficit Hyperactivity Disorder (ADHD) to help them correct unhealthy habits and inappropriate behaviours associated with ADHD. This system is tailored for children diagnosed with ADHD; however, despite its promising aspects, when applied broadly, it may disrupt children without such conditions. Furthermore, this system lacks any notification, alert, or alarm feature to inform their guardians.

In an effort to include the tutor's participation to improve the emotional wellbeing of children, Torddis[2] is introduced as a solution utilising technological advances to monitor students' behaviour while they carry out school tasks independently in their homes and informs the tutors of any developments, so that they can reassure their children that they are not alone. In addition, Torddis is enabled to play sounds that can be personalised messages in accordance with the users' preferences.

To achieve its objectives, Torddis employs advanced computer vision algorithms and deep learning techniques. The system includes a mobile application for tutors and an IoT device that facilitates the analysis of children's behaviour while they engage in school tasks on their own. Developed using the TDDM4IoTS methodology (Guerrero-Ulloa, Hornos and Rodríguez-Domínguez, 2020), Torddis is notable for its holistic approach. It allows tutors to monitor and respond to real-time signs of inattention. Key features include the ability to detect facial expressions that represent fundamental emotions and to identify signs of drowsiness or the inappropriate use of objects during educational activities. This functionality enables tutors to encourage their children to remain focused, utilising both visual and auditory stimuli as motivators (Al-Gburi, Al-Sammak, Marghescu and Oprea, 2023; Enadula, Sriram Enadula and Burri, 2021; Terraza Arciniegas et al., 2022). Torddis's focus on proactive supervision is based on the need to support children during a critical stage of development, providing tutors with a valuable tool to complement traditional home supervision and enhance educational outcomes for this population.

This paper is organised into sections that cover different aspects of the implementation of the current proposal. Section 2 reviews related works published in the last ten years in journals of international impact. These works are indexed in databases such as the Web of Science (WoS), IEEE Xplore, ACM Digital Library, and PubMed. Section 3 describes the materials and methods used throughout the development and evaluation processes of the system. Section 4 presents the main results and discussion, and Section 5 outlines the conclusions and future work.

2. Related Works

In the review of the literature on facial or gesture recognition in students, and its relation to learning in the selected scientific databases, very few studies have been found, suggesting that this field has not been sufficiently investigated. The process of reviewing the state of the art followed the methodology outlined in the scheme of Figure 1.

2.1. Search Questions

This paper explores the critical issue of distraction detection in students as they engage in school tasks independently. With the increase in digital education tools and the necessity for effective learning strategies, understanding how distractions impact student performance has become paramount. The following research questions aim to guide a comprehensive review of related works and inform the development of technological solutions that enhance focus and educational outcomes for children. These questions will help identify the most effective methods and technologies for monitoring and mitigating distractions during educational activities.

- What are the distraction parameters that should be monitored in children during the completion of their school tasks?
- Which computational models are suitable for detecting children's behaviour while they are doing school tasks?
- Which algorithms focused on detecting distractions could be utilised in the development of this proposal?

[2]From Latin "**Tor**queo **d**iscerno **dis**cipulus" meaning "detection of deviation or change in the student's attention."

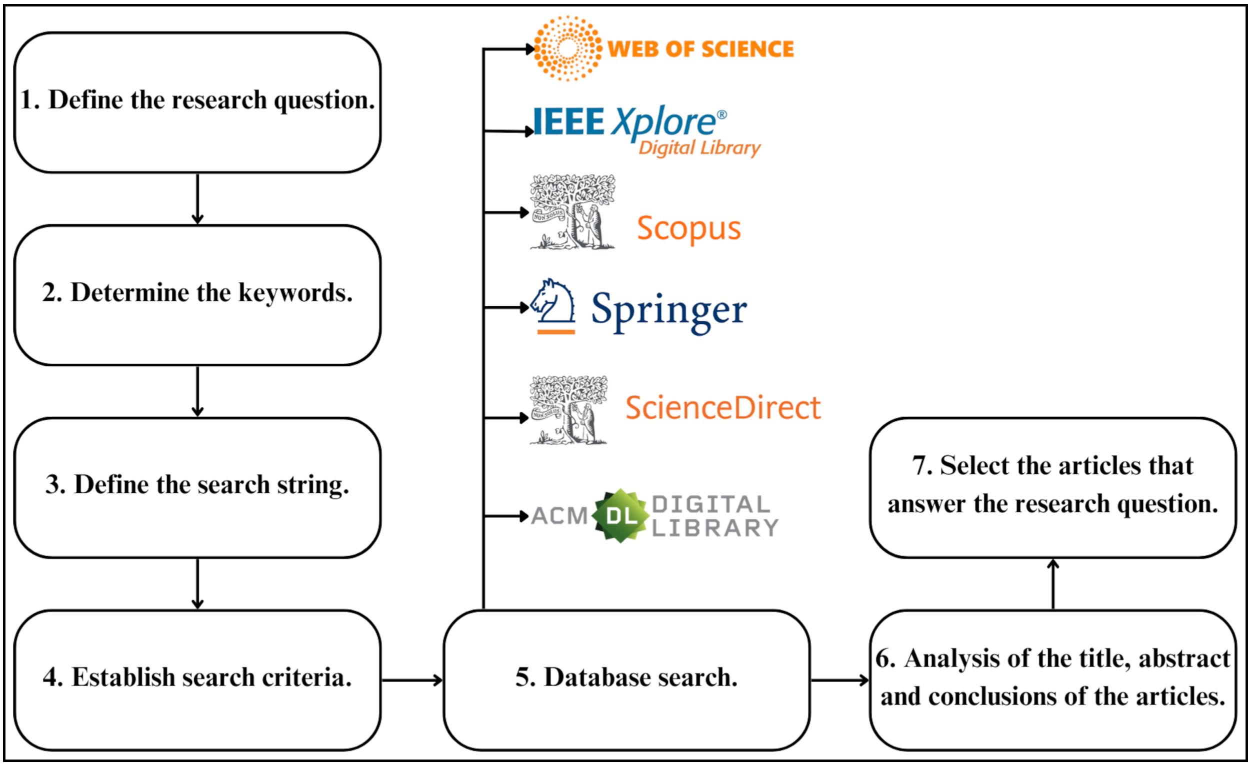


Figure 1: Literature Review Scheme.

Table 1
Search results for related works

Database/Search Engine	Preliminary Results	Final Results
ACM	1	1
IEEE Xplorer	2	1
PubMed	1	0
Scopus	22	18
Web of Science	5	4
Google Scholar	15,400	56

- What hardware and software technologies could be used to develop a prototype device to support children's concentration during school activities?

2.2. Search Strategies

Once the research questions had been defined, we proceeded to select the relevant keywords for retrieving published works from the main databases. These keywords were used to form the search string, which was specifically tailored for each selected scientific database. The search string employed was: ("distraction") AND ("child" OR "children" OR "student" OR "school task" OR "homework") AND ("object recognition" OR "face recognition" OR "facial recognition" OR "gesture recognition").

The databases used included ACM, IEEE Xplorer, PubMed, Scopus and Web of Science. Additionally, Google Scholar was used to broaden the results and thus minimise the possibility of excluding important documents as related work.

2.3. Literature Analysis

In the scientific literature on technologies applied to the educational and childcare sectors, there is a variety of approaches focusing on the use of Artificial Intelligence (AI), the Internet of Things (IoT), and computer vision techniques to enhance learning and behaviour monitoring. Research by Akter, Ali, Khan, Satu, Uddin, Alyami, Ali, Azad and Moni (2021), Albrecht, Foster, Joosten, Falkmer, Tang, Leung, Ordqvist and Falkmer (2014), Berrezueta-Guzman et al. (2021), de Villiers Rader, Zukow-Goldring and Alhanti (2021), Pelc, Kornreich, Foisy and Dan (2006), Washington, Voss, Haber, Tanaka, Daniels, Feinstein, Winograd and Wall (2016), and Warren, Zheng, Das, Young, Swanson, Weitlauf and Sarkar (2015) explore various applications ranging from early diagnosis of autism spectrum disorder to improving emotion recognition in children with attention deficit disorders. All these studies utilise advanced technologies to analyse and respond to specific behaviours of children in controlled or everyday environments, focusing on detecting and responding to the children's particular needs through AI algorithms and connected devices.

Although these research efforts share technological foundations, their specific objectives and methodologies vary significantly. Akter et al. (2021) use transfer learning for diagnosing Autism Spectrum Disorder (ASD) through facial recognition, while Pelc et al. (2006) focus on recognising emotions in children with ADHD using validated photographs, and Albrecht et al. (2014) investigate visual search strategies in children with ASD. Meanwhile, the work by de Villiers Rader et al. (2021) examines how gestures can direct attention to word-object relationships in children with ASD, and Berrezueta-Guzman et al. (2021) assess the use of a robotic assistant to support homework activities in children with ADHD. Each of these studies provides a unique perspective on how technologies can be adapted to address different aspects of learning and social interaction.

Further studies of James and Nettikadan (2019), Hachad, Sadiq and Ghanimi (2020), Enadula et al. (2021) Ozdamli, Aljarrah, Karagozlu and Ababneh (2022), Kulkarni, Anjali, Rohith, Nadagouda and Veeresh (2023), Narkhede, Menon, Mathane, Nikam and Dange (2023), Farsani, Breda and Sebastiá (2020), Boumiza, Bekiarski, Souilem and Pleshkova (2017) and Rocha, Souza, Cardoso, Vijaykumar, Araujo and Frances (2023) illustrate a clear trend towards tusing facial recognition and AI to solve various problems in educational and security environments. Each of them contributes to a broader technological landscape that enhances student interaction and security.

James and Nettikadan (2019) and Hachad et al. (2020) use facial recognition in education in different contexts. James and Nettikadan James and Nettikadan (2019) monitor student security on school buses, whereas Hachad et al. (2020) manage student attendance in classrooms. Both leverage technologies like OpenCV and facial recognition algorithms to address security during transport and efficiency in attendance taking, showcasing the versatility of facial recognition in different educational settings.

Enadula et al. (2021) and Ozdamli et al. (2022) explore emotion recognition in students in online education and distance examinations, respectively. Both employ computer vision technologies to analyse facial expressions, and Ozdamli et al. (2022) also incorporate cheating detection, highlighting the potential of facial recognition to enhance student interaction in virtual environments.

Kulkarni et al. (2023),Narkhede et al. (2023), and Farsani et al. (2020) focus on different applications of facial recognition in tracking attendance and student attention. While Kulkarni et al. (2023) and Narkhede et al. (2023) register attendance, Farsani et al. (2020) examine how teachers' gestures affect students' visual attention, underscoring the utility of advanced technologies in improving both administration and the educational experience.

Boumiza et al. (2017) and Rocha et al. (2023) utilize facial recognition for automated tutoring and monitoring students on school transport in smart cities, respectively. Both emphasize the integrated use of advanced technologies to enhance safety and personalize learning, demonstrating how facial recognition can extend beyond the classroom into broader educational and urban solutions.

Other studies by Nguyen, Binh, Bui and N.T. (2019) and Riquelme, Munita, Jara and Montero (2013) also employ advanced technologies in facial and gesture recognition to assess and enhance student engagement in educational settings. Using systems like YOLOv3, they visually analyse students' responses during class sessions, enabling real-time monitoring and dynamic adjustment of teaching methods to better meet students' needs and emotional states.

Despite technological similarities, approaches and objectives by Nguyen et al. (2019) and by Riquelme et al. (2013) focus on emotion detection and empathy development through mediated reading of children's literature to better understand students' levels of attention and interest. In contrast, Riquelme et al. (2013) recognize postures and gestures to enhance learning adaptability, assessing students' physical interactions with presented content for deeper personalization of the educational experience. Nguyen et al. (2019) create their own dataset for model training, while Riquelme et al. (2013) use transfer learning with pre-trained models to optimize their system.

Table 2
Roles performed by the team members.

Rol	Member
Client/End user	Author 4 and author 5
Project facilitator	Author 3
Development team	Author 1 and author 2
Counsellor	Alternating between author 1 and author 2

The Torddis system emerges in response to the limitations observed in related studies that focus on monitoring student behaviours or emotions using facial and gesture recognition technologies. Unlike these studies, which often limit themselves to assessing emotional or physical responses in more controlled educational settings, Torddis addresses a broader and more complex issue: the distraction of children at home, an environment that is much less structured and predictable. While other studies provide valuable real-time analysis, they generally do not integrate a variety of distraction indicators in their evaluations, nor do they offer interactive and proactive solutions to mitigate the detected distractions. Torddis, however, uses a combination of IoT and AI-driven behaviour analysis to provide comprehensive and multidimensional monitoring that includes facial expression recognition, detection of unauthorized objects, and activity level assessment, thus offering a system capable of adjusting and responding in real time to the specific needs of the home environment.

Furthermore, Torddis is distinguished by its focus on issuing auditory and visual alerts that aim to immediately correct distractions, something that is not common in other reviewed works. These typically focus on data collection and analysis to inform educators or parents after the fact, which can limit the effectiveness of interventions at the crucial moment of distraction. Torddis, on the other hand, is designed to act directly in the context of home learning, where adult supervision may not be constant. This allows the system to not only identify distractions but also actively interact with the child to redirect their attention to school tasks. This proactive approach and its capacity for immediate intervention give Torddis a significant advantage in providing effective and practical support for home education, facilitating a more focused learning environment and less prone to interruptions.

3. Materials and Methods

Torddis was developed using the TDDM4IoTS methodology (Guerrero-Ulloa et al., 2020). This methodology is the most comprehensive with respect to the system lifecycle (Guerrero-Ulloa, Rodríguez-Domínguez and Hornos, 2023e), and has been widely valued (Guerrero-Ulloa, Andrango-Catota, Abad-Alay, Hornos and Rodríguez-Domínguez, 2023a,b; Guerrero-Ulloa, Méndez-García, Torres-Lindao, Zamora-Mecías, Rodríguez-Domínguez and Hornos, 2023d; Guerrero-Ulloa, Fernández-Loor, Moreira, Novais, Rodríguez-Domínguez and Hornos, 2023c). All eleven stages of the methodology were implemented during the development of the technological project, except for the last stage, maintenance, because the system had a very short lifespan at the time of this document's composition. Moreover, this framework aids in the early detection of errors, helping to reduce development costs and time, and allowing for cleaner code (Beck, 2002).

The roles of each of the project team members are shown in Table 2

3.1. Preliminary Analysis

In this stage, an analysis of the preliminary requirements was conducted, encompassing both functional (customer specifications) and non-functional (system quality attributes) aspects at a general level of detail. Use case diagrams were used for the requirements analysis, utilising the free web tool TDDT4IoTS available at https://aplicaciones.uteq.edu.ec or http://www.tddt4iots.com. Additionally, the technology to be used for the development of Torddis was determined, including hardware resources, technologies, and software tools for developing the mobile application and configuring the hardware. The choice of resources was based on the authors' selection criteria, such as the use of open-source software tools and technologies with adequate and sufficient documentation that meet the required functionalities and that the development team has the necessary expertise. Likewise, it was considered important that the IoT hardware be available in the local market, be economical, meet the required functionalities, and have the necessary documentation for its implementation. Although not mandatory, it was also valued that the development team had experience in its configuration and use.

3.1.1. *Method for Facial Expression Recognition*

The method used for facial expression recognition is illustrated in Figure 2. This process requires a photograph as input, which must clearly display a person's face. Subsequently, feature extraction is carried out, and these features are compared using a computational model. This model was trained using a set of images representing the characteristics of seven types of facial expressions. The expressions considered correspond to the basic universal emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral (Zhang and Yu, 2022).

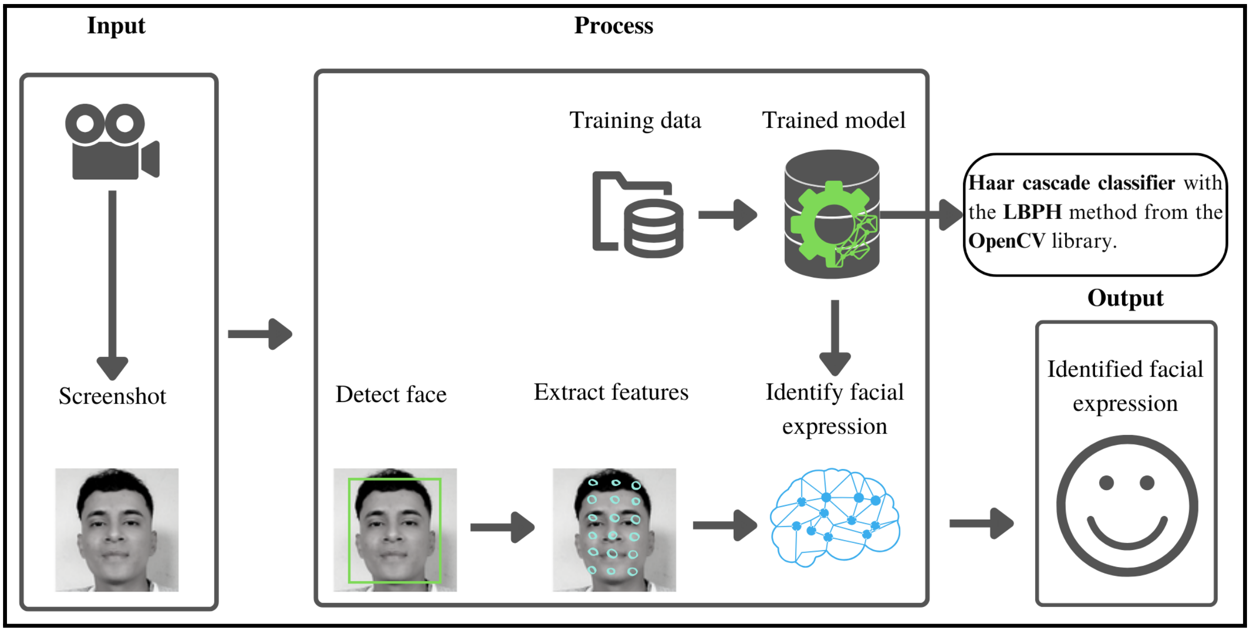


Figure 2: Method for facial expression recognition

3.1.2. *Method for Object Recognition*

This method consists of the following steps: (1) a photograph is taken to capture the objects located on the desk or the area where the infant is working. (2) Image preprocessing is performed, followed by segmentation into parts corresponding to potential objects. (3) Feature extraction is conducted on the segmented image. Finally, the extracted features are compared using a computational model, which was trained with a set of images containing the objects expected to be recognised. Computer vision allows for the automatic detection of the structure and properties of a potential dynamic world in three dimensions, based on one or more two-dimensional images of the world (Cruz, Dimaala, Francisco, Franco, Bandala and Dadios, 2013). Figure 3 illustrates the object recognition method used in the Torddis proposal.

3.1.3. *Distraction Parameters*

To determine the distraction parameters that affect children's concentration during their school activities, a bibliographic review was conducted. Additionally, user opinions and input from an education professional were considered. Table 3 describes the distraction parameters agreed upon by consensus.

3.1.4. *Coarse-Grained Use Case Diagram*

In the general use case diagram (see Figure 4), the functions considered based on the initial interviews with the end-user and educators are shown. The tutor user is the person responsible for configuring the permitted use objects, monitoring their students, issuing alerts to the parents, and persuading the monitored children. Additionally, the tutor user can view the reports and the historical events.

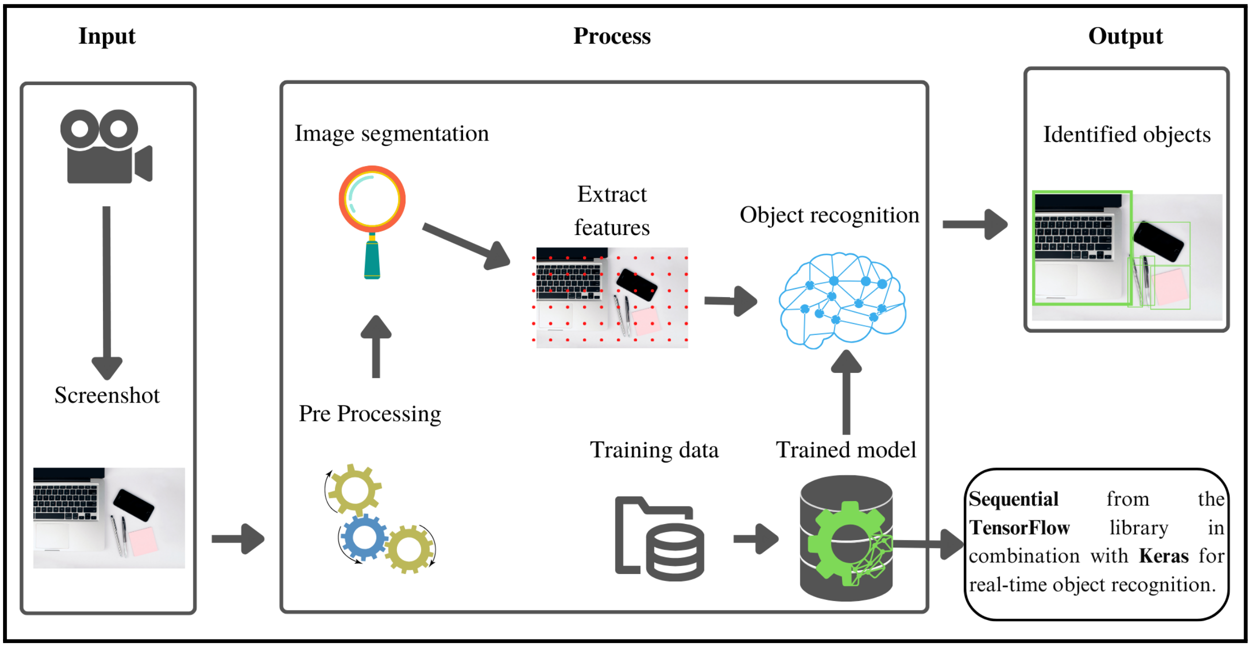


Figure 3: Method for object recognition

Table 3
Distraction Parameters in the Study Area.

Internal Distraction	External Distraction
Expression of emotions such as anger, disgust, fear, happiness, sadness, surprise, and neutral (Asish, Kulshreshth and Borst, 2022; Vettivel, Jeyaratnam, Ravindran, Sumathipala and Amarakecrthi, 2018; Pabba and Kumar, 2022).	Intervention of an unfamiliar person or leaving the study area (Vettivel et al., 2018).
Drowsiness state to determine if the child is awake or asleep (Pabba and Kumar, 2022).	Objects in the study area that divert attention from the activities being performed (Asish et al., 2022; Pabba and Kumar, 2022).

3.1.5. Feasibility Analysis

This project carried out a feasibility analysis in the three aspects considered in the TDDM4IoTS methodology: technical, economic, and operational feasibility. The available hardware and software resources for the development of Torddis were a factor that enabled the success of this project. Additionally, the availability of the development team with the appropriate skills and knowledge ensured that Torddis was completed on time within a very limited budget. The project team managed to recruit a tutor user with an imminent need for a system like the one proposed, which allowed the needs to be analysed in their full spectrum. Furthermore, for its evaluation, a group of tutor users was recruited to verify the requirements proposed during the project's development and to assess the functionality and usability of Torddis. The capabilities of the tutor users were considered to ensure that Torddis remained operable after implementation, and that no personnel would be required, except in cases of corrective maintenance, where individuals with the appropriate knowledge about the development of Torddis would need to intervene.

3.1.6. Technology Analysis

The available technologies for the development of Torddis were analysed, including AI algorithms to monitor students' distraction during their school activities.

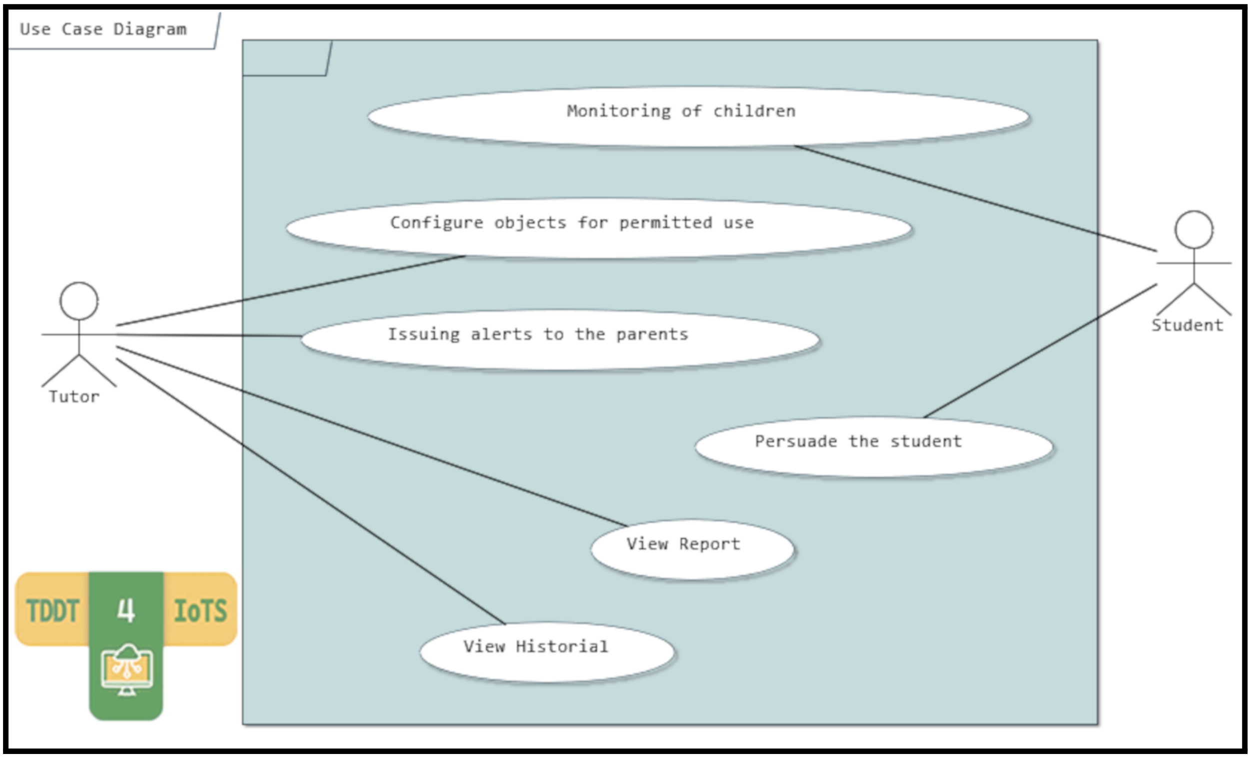


Figure 4: Modelling of user requirements at a high level.

Table 4
Hardware Components

Functionality	Alternatives	Selected	Observation
Connectivity with the web service and video transmission	Ov7670 VGA Camera	Esp32cam	This module has WiFi + Bluetooth connectivity and an integrated video camera (Casas Sanchez, Loayza Apeña, Palomino and Paiva-Peredo, 2022).
Information transmission	Arduino UNO, GSM Module	Esp8266 NodeMcu v3	The NodeMCU module is a small board that provides WiFi connection for data transmission to the web service (Barai, Rysul Kibria Badhon, Zhora and Rahman, 2019).
Alarm sound	Active buzzer	Passive buzzer	Commonly used to generate sound alarms in electronic boards (Adebisi, Adejumobi, Durodola and Jim, 2023).
Light emitter for alert	5mm Red LED	5mm LED (any colour)	A bright transparent LED diode used to set an alarm (Upender, Reddy and Santoshini, 2020).

Hardware Resources

Table 4 describes the IoT hardware resources used to construct Torddis. For the selection of hardware for the construction of the Torddis device, the following criteria were applied: (1) Price: The component to be purchased must be economical. (2) Delivery time: As there is no direct market to acquire it, online stores (www.mercadolibre.com.ec) were searched. The store had to be trustworthy, and the delivery time had to be no more than 48 hours. (3) Expertise: The development team's expertise in using the component, and (4) Documentation: The availability of online documentation for the proper use of the selected component.

Table 5
Software Technologies Used in the Construction of the Torddis System

Functionality	Alternatives	Selected	Observation
Android mobile applications	Kotlin	Java	Language used in Android Studio with a large community in the mobile application development field (Sharma, Bux, Varshney and Tomar, 2021).
AI applications	Java, R	Python	Python is a programming language that has popular open-source libraries for developing AI applications (Cai, Langtangen and Moe, 2005).
Web applications and services in Python	Flask	Django	Popular framework with rapid development capabilities and prevents security errors in web application or service development (V, P, K, P, Khan and Krishna, 2022).
Databases	MySQL, Microsoft SQL Server	PostgreSQL	Robust database with better compatibility with the Django web framework (V et al., 2022).

Software Technologies

The development of the proposed system required the use of various technologies, encompassing programming languages and artificial intelligence algorithms, to effectively support the achievement of the outlined objectives. In Table 5, the software technologies used in the construction of the Torddis system are presented.

Artificial Intelligence Methods for Monitoring Children's Distraction

At this stage, the most suitable AI methods were selected to develop the Torddis proposal. These include methods for:

- Facial recognition,
- Facial expression recognition,
- Sleep detection, and
- Object recognition.

Methods for Facial Recognition

Facial recognition methods focus on face detection, identifying patterns such as eyes, lips, mouth, nose, among other parts. Table 6 lists some methods for detecting faces and performing facial recognition.

The combination of YOLO with MTCNN and FaceNet with SVC is not suitable for the proposed system due to complexity and computational demand. Additionally, Amazon Rekognition was discarded because its cloud processing and customization are not straightforward. Therefore, the selected method was the Haar Cascade classifier with the LBPH method from the OpenCV library, as its customization is simple and the recognition result time is relatively short compared to others.

Methods for Facial Expression Recognition

Facial expression recognition requires an input image to subsequently perform feature extraction that will be compared to a computational model. Table 7 lists some methods for detecting facial expressions.

Based on Table 7, a CNN algorithm was chosen for the development of Torddis due to its accuracy. However, it is important to consider the optimal training of the model. To decide on the most suitable algorithm for implementation in a system, it is necessary to consider that some algorithms' accuracy depends on the dataset used. In the case of MobileNetV2, it was discarded due to its lower accuracy in recognizing facial expressions.

Table 6
Methods for Facial Recognition

Method	Technology and Implementation	Use	Accuracy
Haar Cascade Classifier	*(unspecified)*	Gender classification (Goel and Agarwal, 2012).	98.75%
	OpenCV	Face detection in low-light environments (Le and Mohd, 2022).	81.00%
Amazon Rekognition	AWS	Authentication through facial recognition (Girmay, Samsom and Khattak, 2021).	100%
YOLO and MTCNN, FaceNet and SVC	Google Colab	Facial recognition for attendance control (Darapaneni, Evoori, Vemuri, Arichandrapandian, Karthikeyan, Paduri, Babu and Madhavan, 2020).	99.00%
Local Binary Pattern Histogram (LBPH)	*(unspecified)*	Face detection from captured images (Garcia, Lacayanga and Cruz, 2021).	91.72%

Methods for Object Recognition

Computer vision enables the automatic detection of the structure and properties of a potential dynamic three-dimensional world. First, an input image containing one or more objects is required. Then, image preprocessing is performed to extract features from the segmented image. Table 8 describes a list of algorithms for object recognition.

Based on Table 8, the selected algorithm was Sequential from the TensorFlow library in combination with Keras due to its accuracy, optimal performance, ease of training, and its widespread use for real-time object recognition. MobileNetV2 combined with SSD was discarded due to its lower accuracy in recognizing objects compared to others. Additionally, YOLO was discarded due to the high GPU (Graphics Processing Unit) consumption required for its proper functioning.

Methods for Sleep Detection

The methods for sleep detection require an image containing a face as input. These methods perform preprocessing of the image to extract facial landmarks of the eyes and then analyse whether the person has their eyes closed. Table 9 lists the methods for sleep detection.

Software Tools

With the exception of the operating system on the development team's computers, all other software utilised in the development of Torddis is open-source. Table 10 presents the alternative options considered, along with the rationale for selecting each software.

3.2. Technological Layer Design

Once the initial requirements for Torddis were defined, the IoT system was designed for monitoring infants as they carry out their school tasks independently at home. The architecture of Torddis was developed as a mobile application and an IoT device, where the mobile application is intended for use by parents, representatives, or guardians. The device incorporated an ESP32 CAM, an ESP8266 NodeMcu v3, a Passive Buzzer, a 5mm Red LED, and a Protoboard. The TDDT4IoTS was used to design the Torddis device.

The mobile application was developed in Java, a language widely used for Android applications. Python, a language well-recognized for artificial intelligence applications, was used for the model implementation, and Django for the implementation of web services that provide facial and object recognition functionality.

Figure 5 shows a representation of the Torddis architecture. Firstly, the tutor uses the mobile application which connects to the web server to access the services. Secondly, this server communicates with the Torddis device to receive the child monitoring video. At the same time, the video is processed on the web server using AI algorithms in

Table 7
Methods for Facial Expression Recognition

Method	Data Set	Technology and Implementation	Use	Accuracy
Haar Cascade Classifier	Custom	*(unspecified)*	Recognizes seven expressions: happy, sad, angry, scared, disgusted, surprised, and neutral (Lalitha, Aishwarya, Shivakumar, Srilekha and Kartheek, 2021).	78.00%
	FERC 2013	*(unspecified)*	Detects emotions through facial expressions (Jaiswal, Krishnama Raju and Deb, 2020).	70.14%
CNN	FERC 2013	Python, Keras, Tensorflow, and OpenCV	Recognition of basic human emotions (anger, fear, neutral, happy, sad, surprise, etc.). Implemented for emotion detection (Kedari, Kapile, Kadole and Jaikar, 2021).	60.00%
	FERC 2013	*(unspecified)*	FER classification based on static images (Singh and Nasoz, 2020).	61.70%
	(unspecified)	CNN with 80 epochs	Automatically generates and categorizes questions, evaluates answers, and tracks performance while providing motivational quotes upon detecting student emotions (Silva, Sudasinghe, Hansika, Gamage and Gamage, 2021).	99.00%
	(unspecified)	*(unspecified)*	Recognizes a person's emotions by detecting their face (Bikku, Viswanadha, Madhulatha, Jyothirgamai, Shabana and Sreedevi, 2022).	85.70%
	(unspecified)	*(unspecified)*	Detects a person's emotion through facial expression using an artificial neural network (Kumar and Srivastava, 2021).	89.91%
	JAFFE	*(unspecified)*	Detects emotions through facial expressions (Jaiswal et al., 2020).	97.97%
	CK+	Python, Keras, Tensorflow, and OpenCV	Recognition of basic human emotions (anger, fear, neutral, happy, sad, surprise, etc.) (Kedari et al., 2021).	99.10%
MobileNetV2	*(unspecified)*	Python and TensorFlow	Online evaluation of students' ability to train and implement deep learning solutions (Ilić, Batić, Mirković, Vukmirović, Ćulibrk, Bosakov and Popović, 2021).	60.00%

Python to determine the child's distraction state, and the results are shared through web services. Thirdly, data from the monitoring process is stored in the database, and if a distraction is detected in the child, the device emits an alarm sound and activates an LED light. Finally, the guardian can review the results of the child's distraction monitoring from the mobile application.

3.3. Detailed Requirements Analysis, and Model Generation and Adaptation

The system requirements were detailed through the specification of detailed use cases using the TDDT4IoTS web tool. The writing of the extended use cases corresponding to the system requirements was carried out using the SymLan

Table 8
Algorithms for Object Recognition

Algorithm	Technology and Implementation	Use	Accuracy
YOLO	YOLOv4	Object recognition Liu, Liao, Chou and Fan (2021).	73.01%
	Darknet, YOLOv4 and CNN-2	Defective solar panel detection Zou and V (2022).	100%
	YOLOv4	Vietnamese vehicle detection in real-time Minh, Mai and Minh (2021).	90.00%
	YOLOv4	Vehicle license plate detection in real-time Minh et al. (2021).	92.00%
	Deep Neural Networks (DNN)	Face and object structure detection and analysis in the frame Teja and Kumar (2021).	92.00%
MobileNetV2	Single-Shot multibox Detection (SSD)	Vietnamese vehicle detection in real-time Minh et al. (2021).	85.00%
	SSD	Vehicle license plate detection in real-time Minh et al. (2021).	90.00%
Sequential TensorFlow	Keras	Aerial image classification and detection Sudharshan and Raj (2018).	96.00%

Table 9
Methods for Sleep Detection

Algorithm	Use	Accuracy
MediaPipe Face Mesh	Facial landmark detection with 468 3D points Shanmugam, Badruddin and Asirvadam (2022).	99.87%
Support Vector Machines (SVM)	Eye tracking Altameem, Kumar, Poonia, Kumar and Saudagar (2021).	83.25%
Viola Jones	Drowsiness detection Teja and Kumar (2021).	92.00%
CNN	Trained with 4 gestures such as open eyes, closed eyes, yawning, and not yawning Dia (2021).	80.00%

symbol language. SymLan, implemented in the TDDT4IoTS tool, was used to automatically generate class diagrams using Unified Modeling Language (UML).

Among the most relevant use cases obtained after carrying out a more detailed analysis for each of the deliverables of the Torddis system are those shown in Figure 6.

3.4. Model Generation and Adaptation

By using the TDDT4IoTS tool, the model generation and adaptation, and test generation stages are the phases that consume the least amount of time for developers. Consequently, the model generation and adaptation phase did not significantly impact time resources. Describing each use case with a symbol-based language (non-alphabetic symbols) required verifying the generated diagram to conclude this phase. If any element was missing (due to omission), the use case was reviewed and supplemented to ensure the class diagram was accurate.

The final class diagram, after the last iteration of Torddis development, is shown in Figure 7.

3.5. Test Generation

The purpose of testing is to ensure the quality of the system under development. To achieve this goal, during the development process of Torddis, tests were conducted in two main groups:

- Tests conducted by developers: Unit tests.

Table 10
Software Tools

Functionality	Alternatives	selected	Observation
Create UML diagrams (use case diagram, class diagram) and design the IoT device	Fritzing, Tinkercad, Lucidchart, Diagrams.net	TDDT4IoTS	The only tool that allows creating UML diagrams and designing IoT circuits Guerrero-Ulloa et al. (2023c).
Build the mobile application	Xcode, Eclipse	Android Studio	Official IDE for Android application development Sharma et al. (2021).
Configure Arduino-compatible boards	Visual Studio Code, Visual Studio, Eclipse Arduino IDE	Arduino IDE (and TDDT4IoTS)	A cross-platform IDE for programming Arduino microcontrollers Perumal, A, M, C, Deny and Rajasudharsan (2021).
Manage the system database	pgAdmin III, PGAccess, phpPgAdmin, OpenOffice.org, Red Hat Database graphical tools: RHDB Administrator and Explain Visual, Xpg: Java client for PostgreSQL, Mergeant, Tora: an Oracle tool with some support for PostgreSQL, KNoda, PGInhaler, SQuirreL, AnySQL Maestro, PostgreSQL PHP Generator, WaveMaker Ajax GUI Design Tool	pgAdmin	Provides a variety of advanced data management options, in addition to being the default manager for PostgreSQL Jung, Youn, Bae and Choi (2015).
Edit code for web service development	Sublime Text, Notepad++	Visual Studio Code	Powerful editor that offers a large number of extensions for code writing Vahlbrock, Guddat and Vierjahn (2022).
Version control and collaborative work with a project host (GitHub)	Bitbucket	Git and GitHub	Facilitates collaborative work, allowing workflows that ease the development and maintenance of projects, and is integrated into a large number of development tools Popescu (2015).
Operating system for system development	Linux	Windows 10 Home	Windows 10 has a very intuitive user interface, making it easier to set up the development and testing environment for applications Softić and Vejzović (2022).

- Tests conducted by the client: Functional tests (Deliverable Assessment Stage).

Unit test cases were executed on the generated software to obtain a fully functional product. Part of the unit tests executed during the construction of the Torddis system corresponds to the tests detailed in Tables 11, 12, 13, 14, and 15.

The set of unit tests was generated using the TDDT4IoTS tools. These tests, applied to each of the deliverables developed in each iteration according to the TDDM4IoTS methodology, ensure that Torddis is a product that meets the users' needs.

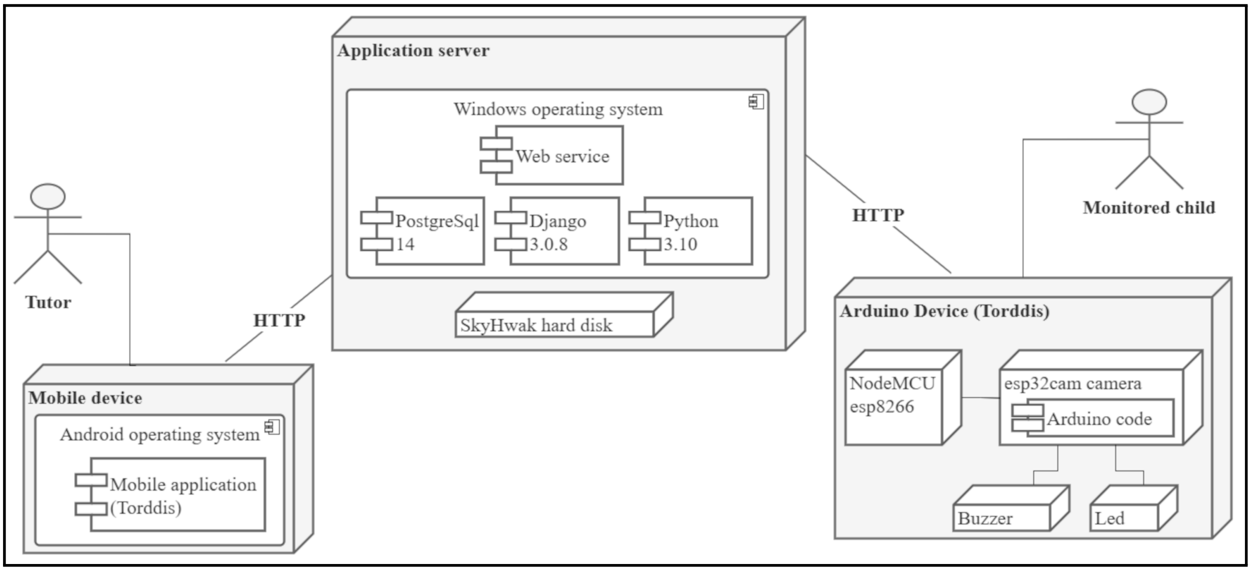


Figure 5: Architecture of the Torddis Child Monitoring System: Integration of Application Server, Mobile Devices, and Arduino Devices for Real-Time Safety.

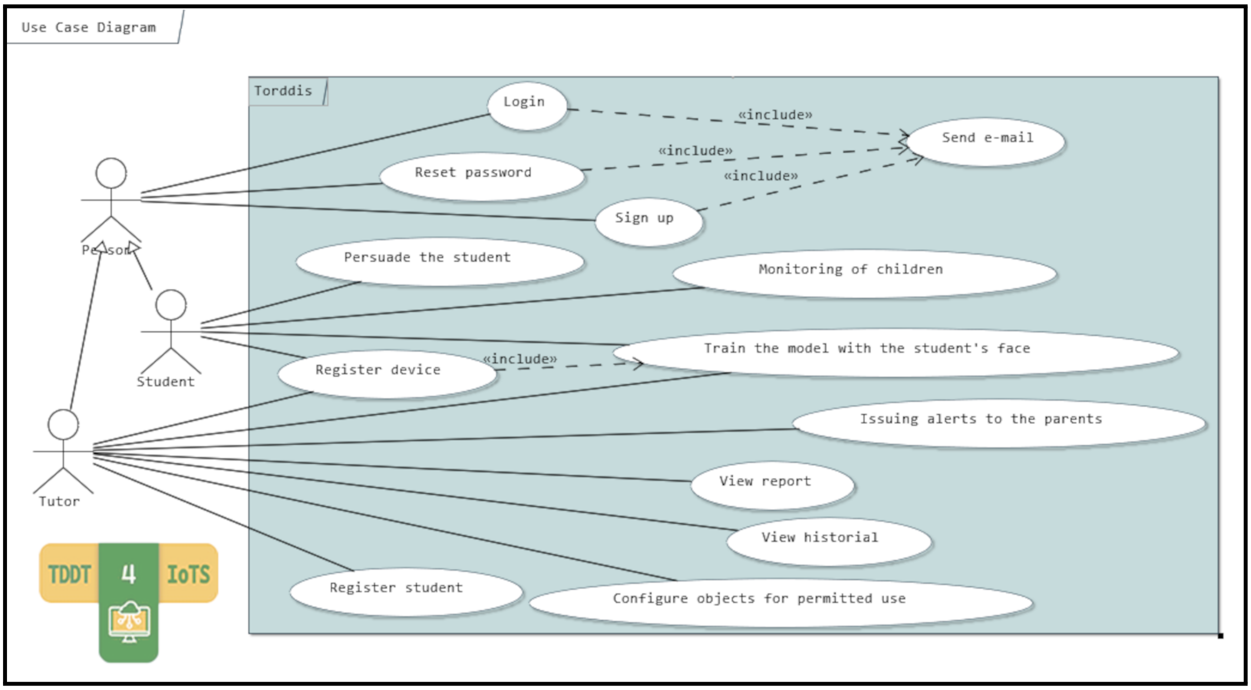


Figure 6: Modelling of user requirements at a detailed level.

3.6. Software Generation

At this stage, the software code was written based on the models and tests generated using the tool. Much of the software was automatically generated with TDDT4IoTS and completed by the developers. For web services development, the Python programming language was used with Visual Studio Code, Java with the Android Studio IDE for the mobile application, and C++ in the Arduino IDE to configure the components of the Torddis device. Once

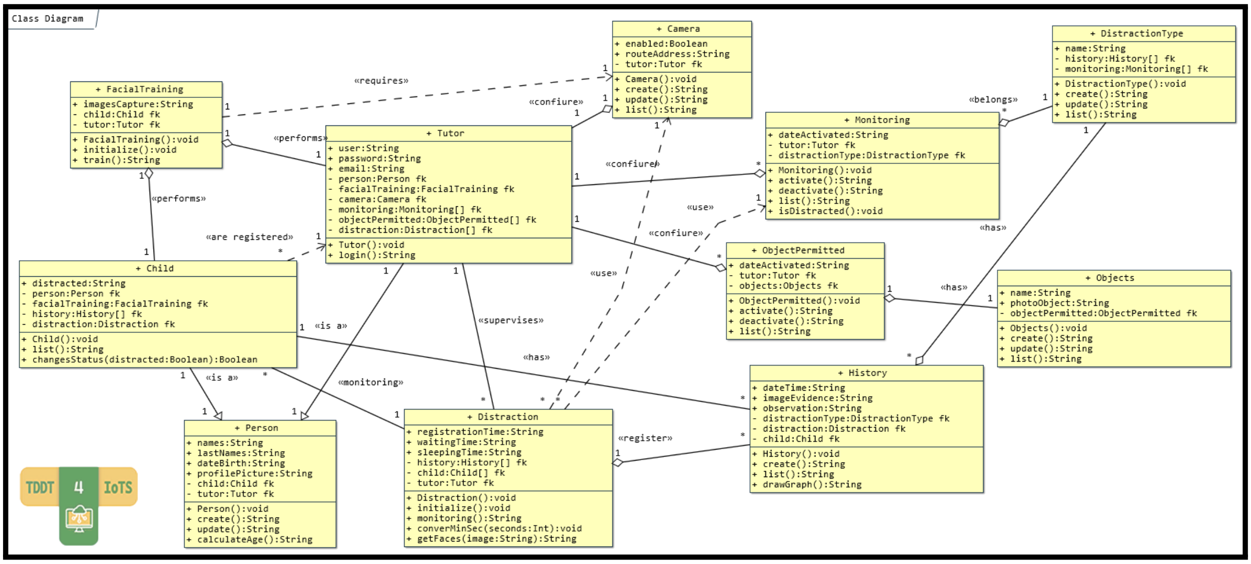


Figure 7: Class Diagram of the Torddis System

Table 11
Test Case Result for Creating Tutor Account

Test Case Result Code:	RPU-1 (see test case Table 16)
Execution Date:	12/12/2022
Obtained Result	
The mobile application successfully created the tutor account.	
Observations	
Improve confirmation messages.	

Table 12
Test Case Result for Logging In

Test Case Result Code:	RPU-2 (see test case Table 17)
Execution Date:	12/12/2022
Obtained Result	
The mobile application successfully logged in and displayed the main menu.	
Observations	
Use a progress bar while validating login credentials.	

the software was generated, both automatically and manually, it was verified to pass all the corresponding tests. In summary, at this stage, a version of the software was obtained for each deliverable, tested and functioning.

Figure 8 shows the project structure of the mobile application using the Android Studio IDE, version 2021.2.1 by Google LLC Studio (2021).

3.7. Model Refinement

This stage is important when the requirements are unclear at the beginning of the development and become more specific as the project lifecycle progresses. In this refinement stage, improved versions of the system models were obtained for each deliverable, providing a more comprehensive solution. In the present project, the initial UML models were updated through the specification of the corresponding use cases, allowing the TDDT4IoTS tool to generate

Table 13
Test Case Result for Face Training

Test Case Result Code:	RPU-3 (see test case Table 18)
Execution Date:	12/12/2022
Obtained Result	
The mobile application successfully trained the child's face.	
Observations	
Display a message when training is completed. Optimise the waiting time during training.	

Table 14
Test Case Result for Device Registration

Test Case Result Code:	RPU-6 (see test case Table 19)
Execution Date:	12/12/2022
Obtained Result	
The mobile application successfully registered the Torddis device.	
Observations	
Display a message when the device registration process is completed.	

Table 15
Test Case Result for Configuring Object Usage

Test Case Result Code:	RPU-7 (see test case Table 20)
Execution Date:	12/12/2022
Obtained Result	
The mobile application successfully activated and deactivated the state of an object.	
Observations	
The object list should be updated with its new state (activated/deactivated).	

an improved model. Additionally, the AI computational models were refined to monitor the children's distraction parameters, adjusting settings such as the number of hidden layers and the training epochs of the model.

3.8. Software Refinement

This refinement stage resulted in improved software, with cleaner and higher quality code compared to the deliverable of the previous stage. The tools used for the software refinement task, with the exception of TDDT4IoTS, were the same as in the software generation stage. The changes made to the software consisted mainly of improvements in the optimal use of memory (temporary or auxiliary variables), in the naming of attributes, methods and classes (project files), and in the inclusion of comments in the most important parts of the code.

3.9. Hardware and Software Deployment

The mobile application, as one of the deliverables, was deployed on an Android version 13 smartphone, Xiaomi Note 10 Pro, to conduct evaluation tests performed by the client (one of the parents of school-age children). This application consumes web services hosted on a web server.

The other deliverable of the Torddis system was the device. This was deployed in a real-ideal environment, where any child can perform school tasks.

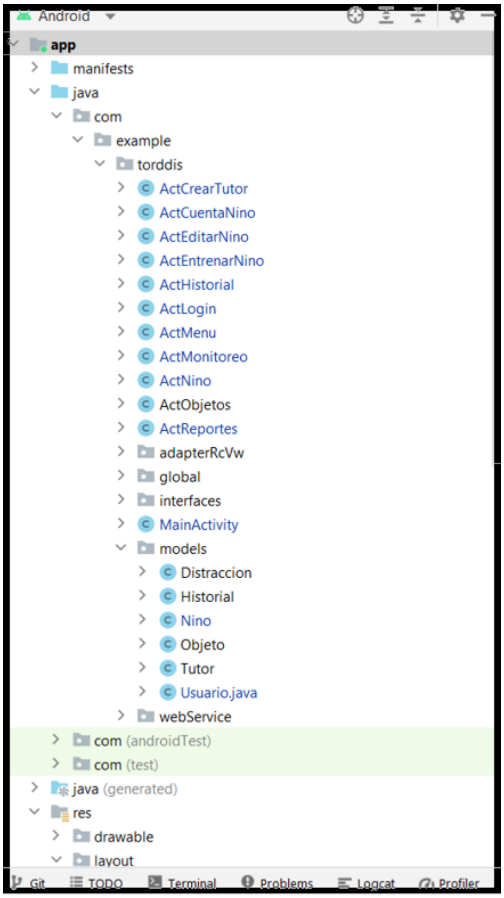


Figure 8: Java classes from the Models package generated with the TDDT4IoTS tool.

3.10. Deliverable Assessment

The tables 16, 17, 18, 19, and 20 show some of the functional test cases executed by the user. These are the test cases with which the user verifies that Torddis meets the requirements specified by them.

3.11. Maintenance

In the project development lifecycle, this phase was not executed due to the short development time for each deliverable, and thus for the project. However, the system must be maintained to function correctly. Table 21 describes some tentative maintenance tasks that should be considered on a quarterly and semi-annual basis, although their frequency may vary depending on the context.

4. Results and Discussion

In this section, the findings obtained through various evaluations conducted on the Torddis prototype system are presented. These evaluations include functional tests, usability questionnaires, and analysis of demographic and monitoring data, aiming to determine the system's effectiveness and acceptance from both a technical perspective and user experience. The results of these evaluations are detailed below, providing a comprehensive view of the performance and utility of the Torddis system in its application context.

4.1. Recognition Analysis

This subsection presents the results of 10 tests conducted using the Torddis system, which evaluated four different recognition tasks: Person, Facial Expression, Sleep Presence, and Distractor Object Recognition. Each test measured

Table 16
Test Case for Creating Tutor Account

Test Case Code:	PU-1
Test Case Name:	Creating Tutor Account
Expected Result:	Successfully create a tutor account
Test Case Procedure	
No.	**Step Description**
1	Open the mobile application.
2	Select the "Sign Up" option.
3	Enter the registration details. • First Name: Carlos Iván • Last Name: Almeida Dueñas • Email: ca884012@gmail.com • Date of Birth: 10/01/2000 • Username: calmeidad • Password: Car12345678*
4	Select the "Create Account" option.

Table 17
Test Case for Logging In

Test Case Code:	PU-2
Test Case Name:	Logging In
Expected Result:	Successfully log in with a tutor account
Test Case Procedure	
No.	**Step Description**
1	Enter the login credentials. - Username: calmeidad - Password: Car12345678*
2	Select the "Log In" option.
3	The mobile application displays the tutor user's menu screen.

the time in seconds it took to recognize the respective subject and recorded whether the recognition was successful. The data collected for this analysis are shown in Table 22.

4.1.1. Results

- **Total recognition time in seconds for all tests**:
  - Persons: 10.56 seconds
  - Facial Expressions: 17.70 seconds
  - Sleep: 41.20 seconds
  - Distractor Objects: 25.62 seconds
- **Number of successful recognitions**:
  - Persons: 13
  - Facial Expressions: 13
  - Sleep: 12
  - Distractor Objects: 11
- **Number of recognition failures**:

Table 18
Test Case for Face Training

Test Case Code:	PU-3
Test Case Name:	Face Training
Expected Result:	Successfully perform facial training for a student
	Test Case Procedure
No.	**Step Description**
1	Enter the "Child" module of the application.
2	Select the "Train" option for a child.
3	Register a device. (see test case Table 19).
4	Select the "Train" option.
5	Position the child's face in front of the device's camera and wait for the facial training process to complete.

Table 19
Test Case for Device Registration

Test Case Code:	PU-4
Test Case Name:	Device Registration
Expected Result:	Successfully register the device with the mobile application
	Test Case Procedure
No.	**Step Description**
1	Select the "Register Device" option.
2	Enter the IP address of the device.
3	Select the "Save" option.

Table 20
Test Case for Configuring Object Usage

Test Case Code:	PU-5
Test Case Name:	Configuring Object Usage
Expected Result:	Successfully configure the use of objects
	Test Case Procedure
No.	**Step Description**
1	Enter the "Objects" module of the application.
2	Search for the object you wish to activate/deactivate.
3	Select the switch control of an object to activate/deactivate it.

- Persons: 1
- Facial Expressions: 1
- Sleep: 2
- Distractor Objects: 3

4.1.2. Average Recognition Time

The average time for successful recognition was calculated for each recognition task:

- **Persons**: $\frac{10.56 \text{ seconds}}{13} \approx 0.81$ seconds
- **facial Expressions**: $\frac{17.70 \text{ seconds}}{13} \approx 1.36$ seconds

Table 21
Definition of Maintenance Tasks

No.	Maintenance Tasks	Quarterly	Semi-annual
1	Internal cleaning of the device.	*	
2	Check if the device components have any imperfections or damage.		*
3	Verify cable connections, cable conditions, connectors, etc.		*
4	Test the functioning of the buzzer and LEDs.	*	
5	Test the IT system (web application server, web services, mobile application, IoT device).		*

Table 22
Aggregate Recognition Results

No.	Persons		Facial Expressions		Sleep Presence		Distractor Objects	
	Latency	Achieved?	Latency	Achieved?	Latency	Achieved?	Latency	Achieved?
1	0.57	Yes	1.50	Yes	5.10	Yes	0.00	**No**
2	0.60	Yes	1.20	Yes	3.50	Yes	1.68	Yes
3	0.00	**No**	0.70	Yes	0.00	**No**	0.00	No
4	0.78	Yes	1.30	Yes	3.68	Yes	1.79	Yes
5	1.02	Yes	0.78	Yes	2.24	Yes	0.00	**No**
6	0.88	Yes	1.01	**No**	2.63	Yes	1.98	Yes
7	0.53	Yes	1.23	Yes	0.00	**No**	1.73	Yes
8	1.20	Yes	0.97	Yes	2.03	Yes	2.05	Yes
9	0.76	Yes	1.05	Yes	4.09	Yes	1.77	Yes
10	1.20	Yes	0.70	Yes	3.36	Yes	1.91	Yes
11	0.69	Yes	1.99	Yes	4.69	Yes	4.27	Yes
12	0.82	Yes	1.83	Yes	3.29	Yes	2.69	Yes
13	0.93	Yes	1.68	Yes	3.14	Yes	2.81	Yes
14	0.58	Yes	1.76	Yes	3.45	Yes	2.94	Yes

- **Sleep**: $\frac{41.20 \text{ seconds}}{12} \approx 3.43$ seconds
- **Distractor Objects**: $\frac{25.62 \text{ seconds}}{11} \approx 2.33$ seconds

4.1.3. Recognition Rate

The recognition rate was determined for each task as the percentage of successful recognitions over the total number of tests:

- **Persons**: 92.86%
- **Facial Expressions**: 92.86%
- **Sleep**: 85.71%
- **Distractor Objects**: 78.57%

4.1.4. Minimum and Maximum Recognition Time

Minimum and maximum recognition times observed across the tests for each task:

- **Persons**:
  - Minimum time: 0.00 seconds (Test 3)
  - Maximum time: 1.20 seconds (Tests 8 and 10)
- **Facial Expressions**:

  - Minimum time: 0.70 seconds (Tests 3 and 10)
  - Maximum time: 1.99 seconds (Test 11)

- **Sleep**:
  - Minimum time: 0.00 seconds (Tests 3 and 7)
  - Maximum time: 5.10 seconds (Test 1)

- **Distractor Objects**:
  - Minimum time: 0.00 seconds (Tests 1, 3, and 5)
  - Maximum time: 4.27 seconds (Test 11)

4.1.5. Distribution of Recognition Times

Recognition times for each task vary, indicating variability in the system's response. Most recognition times are within a reasonable range, suggesting a quick and effective response from the system in most cases.

4.2. Usability Evaluation of the Developed Prototype System

The usability evaluation of the Torddis system was conducted to gather insights on the overall user experience, specifically focusing on the ease of use, the system's interface, and the effectiveness of the features provided. This comprehensive evaluation aimed to identify strengths and areas for improvement, ensuring the system meets the needs of the users effectively. The following sections detail the demographic data of the participants, their experiences with monitoring, the specific tasks performed during the evaluation, and the results from the SUS and open-ended questions (See Appendix C).

4.2.1. Demographic data

At the beginning of the usability evaluation, a demographic questionnaire was administered to gather information about the tutors who participated in the usability evaluation of the finished Torddis system (see Appendix B). The demographic questionnaire yielded the following results:

- A total of 12 families were evaluated: 8 mothers and 4 fathers, all belonging to the geographical area of the authors.
- The average age of the participants is 39 years, with the minimum age being 18 and the maximum age 65 years.
- 58% of the tutors only completed the first level of education, while 42% studied up to secondary education.

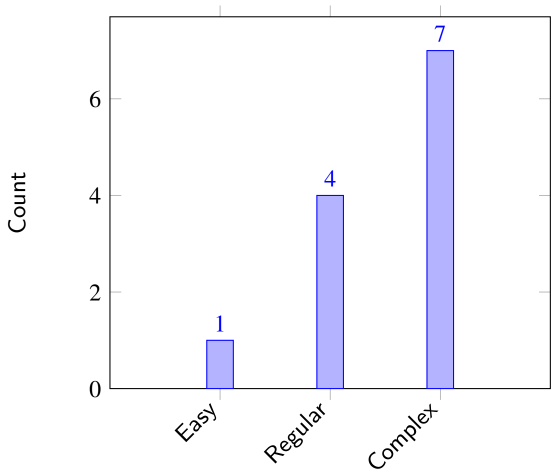
4.2.2. Regarding Monitoring

One of the preliminary questions in the usability evaluation was regarding the ease with which they can monitor their children (elementary school students) while they are doing their schoolwork (see figure 9). For this question, most tutors indicated that the process of monitoring children's distraction is a complex task. Figure 9a shows the detailed results. Another preliminary question was about the frequency with which they need to monitor their children while they are engaged in school activities. Most tutors indicated that they always do so. For more detailed responses, see Figure 9b. Finally, the tutors indicated that among the strategies they use to keep their students focused on their school activities are calls for attention (scolding), motivational advice, and compensation with sweets, toys, trips to the park, favourite foods (see Figure 9c), and other rewards.

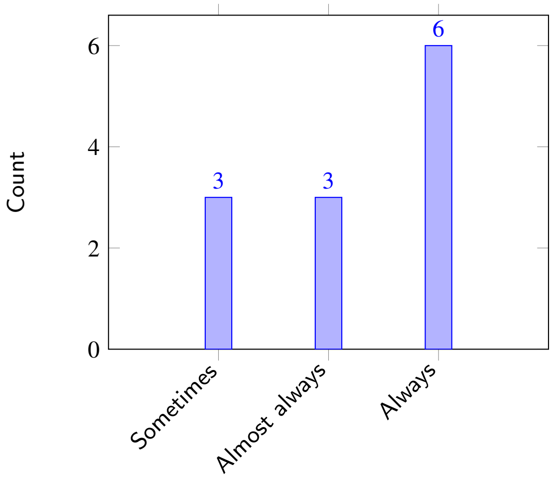
4.2.3. Tasks for Participant Users

The tasks that the tutors performed during the evaluation are as follows:

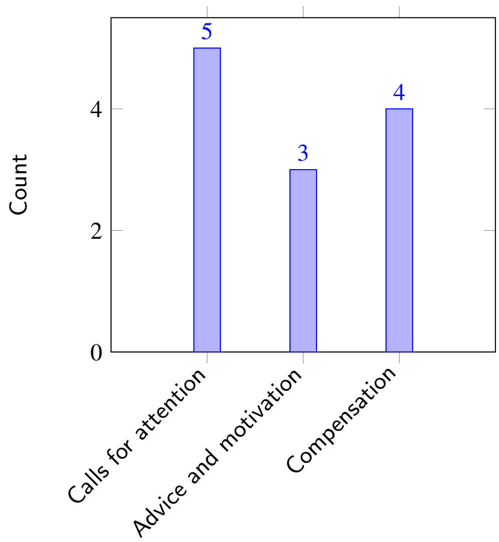
1. Connect the Torddis device to the power supply and place it on the desk where the child will be sitting to perform a task.
2. Create a tutor user account in the mobile application.
3. Log in to the mobile application.
4. Register the child to be monitored.



(a) Monitoring Process of Students



(b) Frequency of Monitoring Students



(c) Strategies to Achieve Concentration

Figure 9: Results of Questions Asked to Parents Regarding the Monitoring Process of Their Elementary School Children While Doing Homework.

5. Register the Torddis device with the mobile application using the IP address provided on a label on the device.
6. Perform facial training for the registered child.
7. Enable and/or disable the objects to be monitored in the objects section of the mobile application.
8. Assign a task to the child while being monitored by the Torddis device: colour a mandala.
9. Activate the recognition of each distraction parameter in the monitoring section of the mobile application.
10. Leave the child alone, without the presence of an adult, for 6 minutes.
11. Enable and/or disable video transmission from the Torddis device.
12. Navigate through the history of the distraction parameters monitored in the child.
13. View the report with graphs of the distraction parameters of the monitored child.

4.2.4. Results of the System Usability Scale Questionnaire

The results analysed in this section correspond to the responses from the SUS questionnaire (see Appendix C.1) administered to the twelve tutor users. After tabulating the obtained data, Figure 10 shows that the mean of the collected data is 81.46% with a standard deviation of 11.65. According to the adjectives (Worst imaginable, Poor, OK, Good, Excellent, Best imaginable) proposed by Bangor et al. Aaron Bangor and Miller (2008) to qualitatively assess the usability of a system based on the achieved mean, it is evident that Torddis has a "Good" level of usability according to the tutor users. Therefore, Torddis has a "Good" level of usability as perceived by the tutor users.

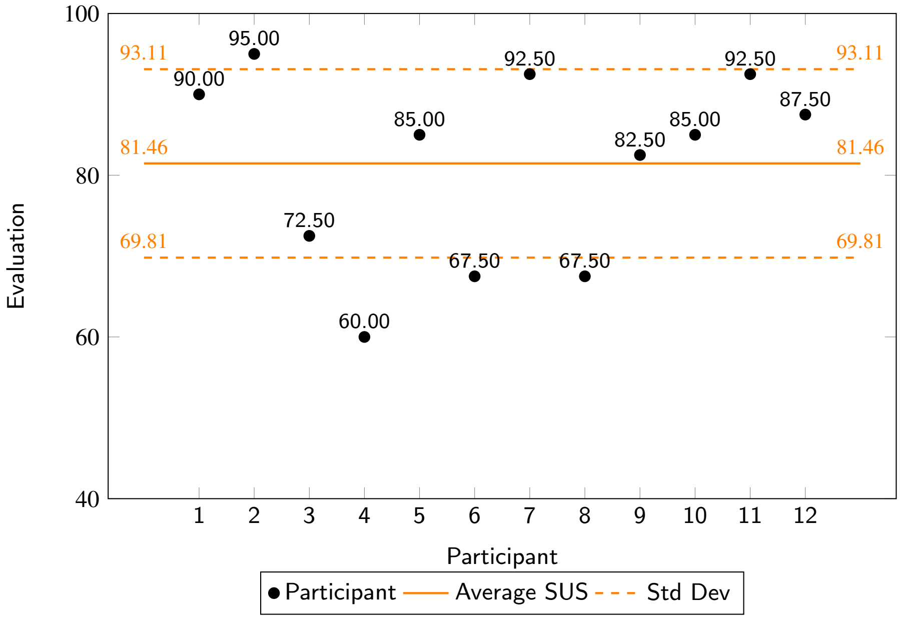


Figure 10: SUS Questionnaire Data by Tutor with Average Evaluation and Standard Deviation

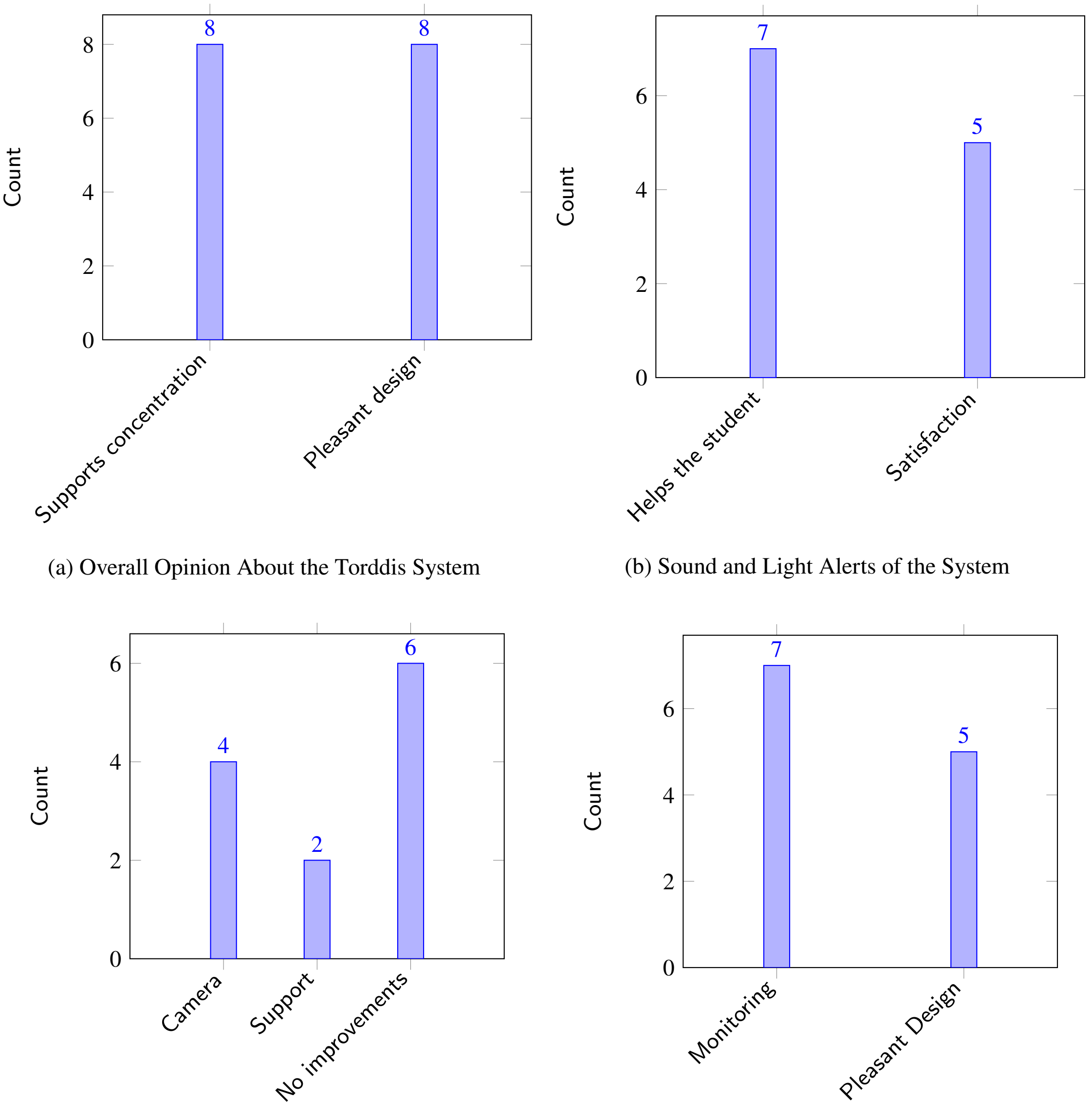
4.2.5. Results of the Open-Ended Questions Questionnaire

At the end of the SUS questionnaire, the tutors answered 8 open-ended questions (see Appendix C.2) to provide their opinions.

"What is your overall opinion of the system?" It was the first question asked, to which the tutors responded that it supports the students' concentration, and others said that it has a pleasant design. The results are shown in Figure 11a. The second open-ended question that the tutors answered was, "Did you find the sounds and/or lights that Torddis uses to be to your liking?" The favourable opinion on this question was because the tutors believe that the light alerts help keep the student awake, and they are satisfied with the sound alarms (see Figure 11b).

In questions 3 (Do you like the design of the Torddis mobile application? Why?), 4 (Is the way your child's distraction monitoring data is visualised in the Torddis mobile application adequate? Why?), 5 (Do you think this system would help improve your child's concentration and keep you informed when they are doing their schoolwork? Why?), and 7 (Would you be willing to continue using the Torddis system?), all tutors expressed positive feedback. They stated that they liked the design of the mobile application screens, highlighted the organization of data in the history and report graphs, confirmed that the prototype system effectively supports children's concentration by keeping them informed when the child is distracted, and indicated their willingness to continue using the Torddis system.

Question 6 provides information indicating the improvements that could be made to Torddis. These include using a higher quality camera, the support on which the device (the camera) is mounted, and a higher percentage mentioned that the device does not need any improvements. These results are shown in Figure 11c. Meanwhile, question 8 gathered the reasons why the Torddis evaluators would recommend using this system for monitoring students during their school activities. Figure 11d shows the reasons mentioned by the tutors. These reasons were that it supports them in monitoring their students, and others mentioned its pleasant design.



(a) Overall Opinion About the Torddis System

(b) Sound and Light Alerts of the System

(c) Suggestions for System Improvements

(d) Reasons to Recommend the System

Figure 11: Results of Questions Asked to Parents Regarding the Monitoring Process of Their Elementary School Children While Doing Homework.

5. Conclusions

The Torddis prototype system has proven to be an effective and well-received tool for monitoring and improving student concentration during their school activities. Evaluations, including functional tests and usability questionnaires, revealed that the system meets the expected technical requirements and is highly appreciated by end-users, namely the tutors.

The analysis of demographic and monitoring data indicates that Torddis significantly impacts managing children's distraction, providing tutors with a valuable tool to keep students focused on their tasks. The high score in the SUS usability questionnaire reinforces the perception that the system is easy to use and effective in its purpose.

The Torddis person recognition system is efficient, with a 92.86% success rate and an average recognition time of approximately 0.81 seconds, demonstrating solid performance under test conditions. Similarly, the facial expression recognition system shows a 92.86% success rate with an average recognition time of approximately 1.36 seconds, highlighting its quick response times and reliability. The sleep presence recognition system is reasonably efficient, achieving an 85.71% success rate and an average recognition time of approximately 3.43 seconds, indicating adequate performance.

The distractor object recognition system, with a 78.57% success rate and an average recognition time of approximately 2.33 seconds, performs adequately under test conditions. It is possible that the tutors' level of education influenced these results, as half of the participants only completed the first level of education, which might have limited their ability to optimise the use of the system.

Additionally, feedback from open-ended questions shows strong support for the system's design and functionality, with valuable suggestions for future developments. Tutors highlighted the importance of visual and auditory alerts to keep students alert and the convenience of the system's configuration and monitoring options.

In conclusion, Torddis has exceeded expectations in terms of functionality and usability, proving to be a viable and effective solution for maintaining student concentration in modern learning environments. The success of this project underscores the importance of technological innovation in education and paves the way for future improvements and expansions of the system.

CRediT authorship contribution statement

Gleistoon Guerrero-Ulloa: Data curation, Methodology, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing,. **Carlos Almeida-Dueñas:** Conceptualization, Data curation, Formal analysis, Investigation, Software, Visualization. **John Plazarte-Suárez:** Conceptualization, Data curation, Formal analysis, Investigation, Software, Visualization. **Orlanzo Erazo-Moreta:** Conceptualization, Data curation, Supervision, Validation, Visualization, Writing – review and editing. **Miguel J. Hornos:** Data curation, Supervision, Validation, Visualization, Writing – review and editing. **Carlos Rodríguez-Domínguez:** Data curation, Supervision, Validation, Visualization, Writing – review and editing.

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A. Informed Consent

Dear Participant,

The purpose of this document is to provide you with the necessary information to decide whether or not to participate in the project titled "Internet of Things-based system for monitoring children's distraction during their academic activities at home", conducted under the direction of Professor Gleiston Cicerón Guerrero Ulloa MDS.

Participation involves using the system provided as directed by the researchers. You will be required to sit in a specific place to use a mobile application. Meanwhile, your child will be monitored by an intelligent device called "Torddis" while performing a specific task directed by the researchers. The participation time is approximately 30 minutes, depending on each participant. These activities will be carried out in one of the researchers' homes.

The information obtained through this study will be kept strictly confidential, and your names will not be used. You have the right to withdraw consent for participation at any time. The study does not involve any risk to you, nor will you receive any compensation. If you have any questions about this project, you can contact us at gguerrero@uteq.edu.ec.

____________________ ____________________ ____________________

Carlos Almeida-Dueñas John Plazarte-Suárez Gleiston Guerrero-Ulloa

After reading the procedure described above, having the researchers explain the procedure, and answering any questions, the participant (undersigned) voluntarily gives their consent to participate in this study.

Participant: ____________________________ Signature: ____________________ Date: ________

B. Demographic Survey

1. Full Name: ____

2. Age: __________

3. Level of Education:

- No education ( )
- Primary ( )
- Secondary ( )
- Higher ( )

4. Gender:

- Male ( )
- Female ( )
- Other ( )

5. How has your experience been as a parent in monitoring your child's distractions while they are doing their schoolwork?

- Easy ( )
- Regular ( )
- Complex ( )
- Very complex ( )

6. How often do you monitor your child's school activities?

- Never ( )
- Sometimes ( )
- Almost always ( )
- Always ( )

7. What strategies have you implemented to improve your child's concentration during their homework?

____

____

Table 23
SUS Questionnaire

Questions	1	2	3	4	5
1. I would like to use the Torddis system frequently.					
2. I found the system unnecessarily complex.					
3. I thought the system was easy to use.					
4. I would need the support of a technician/teacher to use the system.					
5. I found the various functions of the system were well integrated (constituted a whole).					
6. I thought there were too many inconsistencies in the system.					
7. I imagine most people would learn to use the system quickly.					
8. I found the system very difficult to use.					
9. I felt very confident/comfortable using the system.					
10. I need to learn a lot of things before I can use the system.					

Table 24
Open Questions of SUS Questionnaire

No.	Question
1	In general, what is your opinion of the system?
2	Did you like the sounds and/or lights that the Torddis device contains? Please answer yes or no, and provide the reason.
3	Did you like the screen design of the Torddis mobile application? Please answer yes or no, and provide the reason.
4	Do you find the way the distraction monitoring data of your child is visualised in the Torddis mobile application to be adequate? Please answer yes or no, and provide suggestions.
5	Do you think this system would help improve your child's concentration and keep you informed when they are distracted? Please answer yes or no, and provide the reason.
6	Do you think there is anything that should be improved in the Torddis system (Device and Mobile Application)? If so, what?
7	Would you be willing to continue using the Torddis system? Please answer yes or no, and provide the reason.
8	Would you recommend this system to other people interested in monitoring children's distraction while doing schoolwork? Please answer yes or no, and provide the reason.

C. SUS Questionnaire

The questions from the SUS questionnaire using the Likert scale are shown in Table 23, and the open-ended questions are shown in Table 24.

C.1. Questionnaire Likert Scale

C.2. Open Questions of SUS Questionnaire