UNIVERSIDAD DE CASTILLA-LA MANCHA

Tesis Doctoral

# Estudio sobre la utilización de las tecnologías IoT y Wearable en procesos de aprendizaje para mejorar la motivación de los alumnos

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*A mi madre y a mi padre.*
*A mis compañeros de formación profesional.*

# Declaración

Esta tesis doctoral es el resultado de mi trabajo original y no incluye ningún resultado del trabajo realizado en colaboración, excepto cuando se ha indicado específicamente en el texto. No ha sido previamente presentada, parcial o totalmente, en ninguna universidad o institución para ningún título, diploma u otra calificación.
Además, declaro ser uno de los principales autores de todos los trabajos utilizados en esta tesis por compendio de publicaciones, incluyendo los siguientes que han sido publicados en revistas con factor de impacto JCR:

- de la Guía, Elena; López Camacho, Vicente; Orozco-Barbosa, Luis; Brea Luján, Victor.M; Penichet, Victor. M. and Lozano Pérez,María. "Introducing IoT and Wearable Technologies into Task-Based Language Learning for Young Children," in IEEE Transactions on Learning Technologies, vol. 9, no. 4, pp. 366-378, 1 Oct.-Dec. 2016, doi: 10.1109/TLT.2016.2557333. (IF:2.714, Q1)

- López Camacho, Vicente; de la Guía, Elena; Orozco-Barbosa, Luis and Olivares, Teresa. 2020. "WIoTED: An IoT-Based Portable Platform to Support the Learning Process Using Wearable Devices" in Electronics, vol 9, no. 12, Dec 2020, doi: 10.3390/electronics9122071.(IF:2.412, Q2)

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Albacete, Junio 2021

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# Summary

Early school dropout is a relevant problem for current societies and their educational systems. One of the main factors is the lack of motivation of students, which causes their disengagement with the educational process. Detecting the level of motivation of students can help to make strategic decisions to reduce their disengagement. Among the different tools, methodologies, strategies and educational techniques to increase motivation in the learning process, experts propose and positively validate the use of ICT (Information and Communication Technologies) in the classroom. The digital transformation of society, largely driven by the widespread use of mobile devices, smartphones, tablets, wearables, IoT (Internet of Things) devices, etc., also allows transforming educational processes by improving the classical application of ICT.

This thesis focuses on the study, analysis and application of IoT and Wearable technologies in educational activities, with the aim of improving students' motivation. For this purpose, these technologies have been integrated into educational activities with the main function of connecting the user intuitively with the digitized environment. After analyzing, researching and improving the development of the prototype, it has been integrated in different real educational contexts. In this way, data has been collected and the advantages and disadvantages have been analyzed. It has been possible to see how these technologies can help students in two ways. The first, by generating intrinsic motivation in their use, and the second, by the capacity for data collection, detection and analysis of motivation that they offer. For educators, the use of these technologies is beneficial by obtaining automatic records of the tasks performed by each of the students, it also allows educators to create a pleasant environment and encourage student participation.

This thesis presents a software and hardware platform design that integrates IoT and Wearable technologies to conduct and support educational activities. One of the main goal has been set on the integrated design, implementation, and validation of a custom-made wearable device for the interaction of students with IoT smart objects. Thanks to the advances made in recent years in the miniaturization of electronic components, it has been possible to incorporate the communication and sensing technologies necessary for its use in the classroom. The platform and the device have been designed and validated by involving the end-user, students and educators, and individuals with special needs in a continuous development cycle through numerous evaluations. The thesis reports the results obtained during various campaigns covering a complete operational validation in terms of effectiveness in learning activities, usability, and user satisfaction.

On the other hand, the use of Learning Analytics (LA) and Multi Modal Learning Analytics methodologies (MMLA) is a field with a key role in educational institutions in the coming years. It can help make strategic decisions to reduce learner disengagement. Leveraging the data capture capabilities of IoT and Wearable technologies, this thesis has analyzed, through a long-term study during a full academic year, how to apply Multi Modal Learning Analytics for the detection of student motivation. A taxonomy of behavioral patterns has been defined on how learners interact with the platform when performing educational activities. With this taxonomy, the captured data and the use of techniques based on Machine Learning, a model has been obtained that is able to determine whether or not students are motivated when using the platform. This allows the educator to take the appropriate measures in order to increase the motivation of students in the activity, and avoid their disengagement.

Therefore, the platform developed based on the new wearable device, designed for an IoT environment, can support teachers in the educational process, helping to determine the motivation of students, a key factor against school dropout. The platform is open, low cost and has been developed taking into account the main agents of the educational system such as students and teachers.

# Resumen

El abandono escolar temprano es un problema importante de las sociedades actuales y sus sistemas educativos. Uno de las factores principales es la falta de motivación de los alumnos, lo que provoca su desvinculación con el proceso educativo. Detectar el nivel de motivación de los alumnos puede ayudar a tomar decisiones estratégicas para reducir su desvinculación. Entre las diferentes herramientas, metodologías, estrategias y técnicas educativas para aumentar la motivación en el proceso de aprendizaje, los expertos proponen y validan de forma positiva el uso de las TIC (Tecnologías de la información y la comunicación) en el aula. La transformación digital de la sociedad, impulsada en gran medida por el uso generalizado de dispositivos móviles, teléfonos inteligentes, tabletas, *wearables* (dispositivo que se puede llevar en le cuerpo), aparatos IoT (Internet of Things), etc., también permite trasformar los procesos educativos mejorando la aplicación clásica de las TIC.

Esta tesis se centra en el estudio, análisis y aplicación de las tecnologías *IoT y Wearable* en actividades educativas, con el objetivo de mejorar la motivación de los alumnos. Para ello, se han integrado estas tecnologías en actividades educativas con la función principal de conectar al usuario de forma intuitiva con el entorno digitalizado. Después de analizar, investigar y mejorar el desarrollo del prototipo se ha integrado en diferentes contextos educativos reales. De esta forma, se han recogido datos y se han analizado las ventajas y desventajas. Se ha podido ver cómo estas tecnologías pueden ayudar a los alumnos en dos sentidos. El primero, por la generación de motivación intrínseca en su uso, y el segundo, por la capacidad de recolección de datos, detección y análisis de la motivación que ofrecen. Para los educadores, el uso de estas tecnologías resulta beneficioso al obtener registros automáticos de las tareas realizadas por cada uno de los alumnos, también permite a los educadores crear un ambiente agradable y fomentar la participación de los alumnos.

Esta tesis presenta el diseño de una plataforma de software y hardware que integra las tecnologías *IoT y Wearable* para realizar y apoyar actividades educativas. Uno de los objetivos principales se ha fijado en el diseño integrado, la implementación y la validación de un dispositivo wearable a medida para la interacción de los estudiantes con objetos inteligentes *IoT*. Gracias a los avances realizados en los últimos años en la miniaturización de los componentes electrónicos, ha sido posible incorporar las tecnologías de comunicación y sensorización necesarias para su uso en el aula. La plataforma y el dispositivo han sido diseñados y validados involucrando al usuario final, a los estudiantes y educadores, y a las personas con necesidades especiales en un ciclo de desarrollo continuo a través de numerosas evaluaciones. La tesis presenta los resultados obtenidos durante varias campañas

de evaluación que cubren una completa validación operativa en términos de efectividad en las actividades de aprendizaje, usabilidad y satisfacción del usuario.

Por otro lado, el uso de las metodologías de *Learning Analytics* y *Multi Modal Learning Analytics* es un campo con un papel clave en las instituciones educativas en los próximos años. Puede ayudar a tomar decisiones estratégicas para reducir la desvinculación de los estudiantes. Aprovechando las capacidades de captura de datos de las tecnologías *IoT y Wearable*, en esta tesis se ha analizado, a través de un estudio a largo plazo durante un curso académico completo, cómo aplicar *Multi Modal Learning Analytics* para la detección de la motivación de los alumnos. Se ha definido una taxonomía de patrones de comportamiento sobre cómo los alumnos interaccionan con la plataforma cuando realizan las actividades educativas. Con esta taxonomía, los datos capturados y el uso de técnicas basadas en *Machine Learning*, se ha obtenido un modelo que es capaz de determinar si los alumnos están o no motivados cuando utilizan la plataforma. Esto permite al educador tomar las medidas oportunas con el fin de aumentar la motivación de los alumnos en la actividad, y evitar su desvinculación.

Por tanto, la plataforma desarrollada basada en el nuevo dispositivo *Wearable*, diseñado para un escenario *IoT*, puede dar soporte a las profesores en el proceso educativo, ayudando a determinar la motivación de los alumnos, factor clave contra el abandono escolar. La plataforma es abierta, de bajo coste y ha sido desarrollada teniendo en cuenta a los agentes principales del sistema educativo como son los alumnos y los profesores.

# Agradecimientos

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# Acrónimos

| | |
|---|---|
| BLE | Bluetooth Low Energy |
| HTML | HyperText Markup Language |
| ICT | Information and Communication Technology |
| IoT | Internet of Things |
| JCR | Journal Citation Reports |
| LA | Learning Analytics |
| ML | Machine Learning |
| MMLA | Multi Modal Learning Analytics |
| NFC | Near Field Communication |
| SoC | System on a Chip |
| RQ | Research Question |
| TIC | Tecnologías de la Información y la Comunicación |
| WiFi | Wireless Fidelity |

# Indice

CAPÍTULO 1

# Introducción

Este capítulo presenta los elementos principales de esta tesis. En la sección 1.1 se expone la justificación y la motivación para realizar un estudio sobre la utilización de las tecnologías *IoT y Wearable* en procesos de aprendizaje con el fin de mejorar la motivación de los alumnos. La sección 1.2 describe los objetivos y las cuestiones de investigación propuestas en esta tesis. La sección 1.3 describe el plan de trabajo y la metodología a través del planteamiento y logro de objetivos. Por último, se detalla la estructura de esta tesis en el apartado 1.4.

## 1.1 Justificación y motivación

### 1.1.1 Visión general

El abandono escolar prematuro es el indicador que se considera más importante sobre el riesgo de exclusión de la población joven. Reduce la competitividad, la productividad, y resulta un gran obstáculo para el crecimiento económico y el empleo. Los jóvenes que abandonan prematuramente la educación se caracterizan por una falta de capacidades y cualificaciones, y están expuestos a un riesgo mayor de desempleo, exclusión social y pobreza. Para la Unión Europea minimizar las tasas de abandono escolar es una prioridad. Por la curva generacional, la población activa de la Unión Europea se reduce cada vez más por lo que es necesario aprovechar al máximo sus recursos humanos [32].

España con 17,3%, según los datos publicados en Eurostat en 2019 [14], es el país con mayor tasa de abandono escolar de la Unión Europea. Esta tasa se ha ido reduciendo de forma paulatina desde el 30,3% de 2006, primer año en que Eurostat publicó estos datos, pero está lejos de cumplir el objetivo del 10% que marcó como objetivo la Unión Europea para 2020.

Uno de los factores más importantes que predicen el abandono escolar es la falta de motivación, *engagement* en terminología inglesa, y la desvinculación con la escuela que esto genera [19]. La organización estadounidense sin ánimo de lucro para la mejora del sistema educativo denominada *greatschoolspartnership* (greatschoolspartnership), define la motivación o *engagement* como "el grado de atención, curiosidad, interés, optimismo y pasión que los alumnos muestran cuando están aprendiendo o se les enseña" [1].

Los alumnos con motivación tienen unos indicadores altos de atención, de participación activa en las actividades educativas, de compromiso emocional y de sentimiento de protagonismo en el proceso de aprendizaje. No se limitan solo a participar en las actividades, sino que tienen conciencia del objetivo a cumplir, lo que les involucra en su propio aprendizaje, además de tener desarrollado un sentido alto de pertenencia al grupo [19].

El proceso de aprendizaje de un alumno motivado va más allá de la simple exigencia para aprobar un examen o completar una actividad en particular. Un alumno con motivación muestra claramente sus ganas de querer aprender, se interesa, participa activamente en las actividades y muestra una intención real de comprender los contenidos. Por el contrario, los alumnos desmotivados o sin motivación se caracterizan principalmente por la falta de implicación, desinterés en los contenidos, y tienen una participación limitada en las actividades educativas. La ausencia de motivación se puede observar desde cuatro indicadores: el emocional, el cognitivo, el conductual y el social. El indicador emocional muestra cómo los alumnos tienen una reacción negativa, frustración y aburrimiento. El indicador cognitivo refleja el reto que representa para los alumnos asimilar ideas complejas. El indicador conductual está relacionado con el comportamiento disruptivo o el incumplimiento de las normas del aula, y el indicador social tiene que ver con la colaboración e interacción social con los compañeros [21].

Identificar la falta de motivación, y la desvinculación con la escuela que todo ello conlleva, puede ayudar a los educadores a establecer estrategias y metodologías que estimulen a los alumnos. Con esto, se minimizaría en un primer momento el absentismo y el posterior abandono escolar.

En este sentido, generar motivación en los alumnos requiere la puesta en práctica de estrategias y actividades adecuadas para involucrarlos en el proceso de aprendizaje, rompiendo con el enfoque tradicional que se limita a transmitir la información.

Entre las diferentes herramientas, metodologías, estrategias y técnicas educativas para aumentar la motivación de los alumnos, los expertos proponen como muy válidas el uso de las nuevas tecnologías TIC en el aula. El quinto estudio sobre el uso de la tecnología en la educación de Blinklearning [7], en el que han participado más de 3000 docentes de España y Latinoamérica, concluye que la motivación de los jóvenes por el uso de las TIC es alta o muy alta en un 67%. La utilización de estas tecnologías ayudaría a evitar la sensación de frustración y desconexión, aumentando en consecuencia la motivación de los alumnos en los procesos educativos. Las actividades de aprendizaje con TIC pueden mejorar la motivación usando diferentes herramientas, y permiten crear actividades novedosas utilizando un contenido variado de recursos. Las presentaciones multimedia, el uso de pizarras digitales interactivas, la utilización de entornos de realidad virtual,etc. contribuye a hacer las actividades educativas más interesantes y relevantes para los alumnos evitando la pérdida de concentración. Las TIC también pueden mejorar la dinámica de la exposición de los contenidos mejorando la atención de los alumnos, permitiendo una adaptación más fácil a diferentes contextos de aprendizaje. El educador se puede beneficiar de las posibilidades que ofrecen las TIC para la creación y difusión de contenidos propios y personalizados en función de las necesidades de cada alumno. Pueden proporcionar a los alumnos contenidos más interactivos, participativos y creativos de los que proporcionan solo la utilización de los libros de texto. Además, el utilizar las TIC permite que los alumnos se vayan preparando para un entorno en el que el uso de la tecnología es cada día más habitual. También se favorece la comunicación entre el educador y el alumno.

### 1.1.2 Tecnologías IoT y Wearable en el aula

Con tecnologías como las interfaces de usuario tangibles, la realidad aumentada, la robótica interactiva o los teléfonos móviles inteligentes, el panorama educativo se está transformando rápidamente, dando lugar a nuevas herramientas de aprendizaje y enseñanza que permiten a los alumnos utilizar una gran variedad de dispositivos y aplicaciones [18, 37].

Tradicionalmente las TIC más habituales en el aula han sido los ordenadores de sobremesa, portátiles e incluso las videoconsolas [8, 22]. Las ventajas que ofrecen estas plataformas en el aula son numerosas, potencian las actitudes positivas de los alumnos y resultan atractivas proporcionando información casi ilimitada con solo pulsar un botón. Sin embargo, su uso requiere que los alumnos permanezcan en un mismo lugar mirando las pantallas de estos dispositivos, un factor que inhibe la interacción y la colaboración directa entre los alumnos en el aula pudiendo afectar al nivel de motivación.

En los últimos años, ha aumentado el interés por las técnicas de enseñanza basadas en tareas, éstas hacen hincapié en la comunicación y el uso práctico de lo enseñado, alejándose así de los métodos repetitivos [5]. Dentro de este enfoque, la importancia de situar a los alumnos en escenarios del mundo real en los que puedan aprender de forma práctica se ha convertido en una prioridad importante para muchos educadores. Este enfoque es especialmente relevante en el contexto de la enseñanza de lenguas extranjeras [10], pero es extensible a otras materias. La interacción a través de recreaciones de escenarios del mundo real en los que alcanzar determinados objetivos o tareas tiene un gran potencial para apoyar el aprendizaje debido a la participación práctica y activa. En comparación con otras técnicas, el aprendizaje basado en tareas tiene el potencial de mejorar la experiencia educativa y las actividades creativas de resolución de problemas llevando a los alumnos al siguiente nivel de aprendizaje [10], generando niveles altos de motivación. El uso de las TIC es de gran ayuda para la recreación de estos escenarios, además de que puede minimizar la carga cognitiva, mejorando el aprendizaje y la colaboración de los alumnos. La computación ubicua, la computación omnipresente, Internet, las tecnologías de detección, las tecnologías de comunicación y los dispositivos integrados pueden fusionarse para crear escenarios en los que el mundo real y el digital se encuentren e interactúen simbióticamente [29].

La popularidad de los *smartphones* y las *tablets* ha aumentado en los últimos años como solución alternativa o complementaria para apoyar las actividades de aprendizaje y enseñanza en el aula. Estos dispositivos presentan muchas ventajas como son la facilidad de uso, portabilidad, versatilidad, adaptabilidad y capacidad de personalizar las experiencias individuales. En los procesos y actividades de educación, los *smartphones* y *tablets* permiten superar los límites temporales y físicos del aula, ya que la información que proporcionan es omnipresente y ya no se limita a un tiempo y lugar específicos [18]. Muchos estudios recientes exploran los beneficios, la idoneidad y los posibles riesgos de utilizar los *smartphones* como vehículo para las actividades educativas. De hecho, numerosos estudios han descubierto que los *smartphones* pueden tener un impacto negativo en el aprendizaje a través de la distracción o el aislamiento [23].

Como complemento o alternativa al uso de los *smartphones* y *tablets* en el aula surge la utilización de tecnologías vestibles (basadas en dispositivos que se pueden llevar en el cuerpo), tecnología *wearable* en terminología inglesa, y la de Internet de las cosas (IoT). Estas tecnologías surgen de la miniaturización de los sistemas y de la utilización de tecnologías de comunicación que posibilitan la movilidad como son la WiFi (Wireless Fidelity) y el *Bluetooth Low Energy*(BLE) [25].Estas tecnologías tienen el potencial de transformar completamente el aula mediante la utilización de objetos inteligentes basados en IoT y la interacción con estos mediante *wearables* [36]. Estos objetos inteligentes pueden estar basados desde la tecnología *Near Field Communication* (NFC) [26], una de las tecnologías posibilitadoras del IoT, hasta sistemas basados en sistemas *System on a Chip* (SoC) [28] con capacidad de procesamiento de datos y dotados de múltiples sensores, actuadores y mecanismos de comunicación. Sin embargo, el uso de estas tecnologías todavía tiene mucho camino que recorrer para ser utilizadas de forma generalizada en las actividades educativas. La mayoría de las plataformas educativas actuales basadas en *wearables* están dirigidas a asignaturas específicas, como la educación física, la informática, etc. En un estudio realizado por Lindberg, Seo y Laine [27], se evalúa una plataforma orientada a la educación física que se basan en el uso de dispositivos que favorecen la movilidad y la monitorización, como son los *wearables* (pulseras de actividad) y los *smartphones*. Estos dispositivos permiten realizar, lo que se conoce en terminología inglesa como *exergames*, y que son una combinación de ejercicio físico con juegos, y tienen como objetivo aumentar la motivación. Los alumnos durante los *exergames* son monitorizados a nivel de actividad y a nivel de movimientos, esto permite una posterior evaluación por parte de los educadores. Otro enfoque centrado en la enseñanza de informática [34], se basa en la utilización pedagógica de un kit de tecnologías *IoT y Wearable* diseñado para introducir a los alumnos en los fundamentos estas tecnologías, incluyendo la integración de sistemas y los principios de programación.

Sula et al. realizaron un estudio [40] en el que introducen una plataforma *IoT* para apoyar y evaluar las habilidades en matemáticas de alumnos diagnosticados con autismo. Esta plataforma se basa en un dispositivo *IoT* multisensorial con el que los alumnos realizan las actividades a través de objetos inteligentes. Este dispositivo además monitoriza el nivel de concentración y excitación de cada alumno. En función de esta monitorización, la plataforma es capaz de actuar sobre parámetros ambientales como luz de ambiente, sonidos relajantes, temperatura, etc. con el fin de mantener la atención del alumno mediante la obtención de la ventana de estado de calma-alerta en la que se maximiza la capacidad concentración. Todos estos trabajos muestran como con estas tecnologías la información es dinámica e instantánea, permitiendo la movilidad y la retroalimentación continua. Si bien, hasta la fecha, no se han realizado estudios sobre el diseño, evaluación y adecuación de una plataforma educativa *IoT y Wearable* diseñada como una plataforma global.

Una plataforma *IoT y Wearable* puede ser aplicable a todas las etapas de la educación pero será de especial interés en las etapas tempranas. Es en estas cuando los alumnos aprenden basándose en la experiencia y en la interacción continua con su entorno, incluidos sus compañeros. El uso de objetos inteligentes *IoT y wearables* además puede facilitar la comunicación entre los alumnos y los educadores, mediante la retroalimentación que ofrece una plataforma de estas características. La plataforma podrá registrar y analizar datos administrativos, de control, de aprendizaje, etc. Se tendrá de forma automática información de asistencia, logros, dificultades, nivel de participación de cada estudiante, etc. [4, 38]. Todos estos datos, con el adecuado procesamiento, pueden ser de gran ayuda en la detección del nivel de motivación de los alumnos para poder adaptar las actividades educativas de la forma más apropiada.

### 1.1.3 Analítica del aprendizaje y análisis multimodal

Se conoce como analítica del aprendizaje, *Learning Analytics* (LA) en terminología inglesa, a la medición, recopilación, análisis y presentación de datos de los alumnos en el contexto de las actividades educativas, con el fin de comprender y optimizar los procesos educativos [39].

*Learning Analytics* surge de la digitalización de la educación y la facilidad que esto proporciona en cuanto a recolección y análisis de datos. Con el uso de plataformas educativas tipo Moodle [3], los alumnos dejan un rastro digital sobre su participación en las actividades que se desarrollan en estas plataformas. Se puede fácilmente recolectar y analizar número de accesos, horarios de conexión, tareas realizadas, participación e interacción en los foros, etc.

La información que proporcionan las técnicas y métodos de *Learning Analytics* puede considerarse muy valiosa para cualquier profesor, ya que le permitirá conocer la evolución de cada alumno, su comportamiento y su progreso en el aprendizaje. Y lo que es más importante, podrán detectar la falta de motivación de los alumnos. Si este diagnóstico se realiza a tiempo, podrán reformular la estrategia de enseñanza con el objetivo de fomentar la implicación de estos alumnos concretos.

La utilización de estas técnicas y métodos se lleva acabo a través de lo que se conoce como ciclo de *Learning Analytics* que se compone de cuatro procesos que se retroalimentan [12]: recolección, modelado, presentación e intervención. El primer proceso es el de recolección de los datos que pueden provenir de diferentes fuentes dentro del proceso educativo. Se pueden recolectar datos de carácter administrativo como pueden ser los demográficos, socioeconómicos, etc. obtenidos de la información de matriculación del alumnado. Por otro lado, los datos directamente recolectados de la actividades educativas, como resultados, logros, interacciones, participación, etc. El segundo proceso es de modelado, mediante métodos estadísticos y de aprendizaje automático o *Machine Learning* (ML), se analizan los datos en busca de patrones tendencias, resultados globales y particulares de las actividades, análisis predictivo, etc. El tercer proceso es en el que se presentan los datos miembros de la comunidad educativa como son los educadores, coordinadores, directores e incluso a los alumnos. Por último, el proceso de intervención que consiste en todas las acciones y estrategias que se realizan para mejorar los procesos educativos en función de los datos recopilados.

En el proceso de recolección, dentro del ciclo de *Learning Analytics*, también se puede ampliar con la recolección de datos multi modales mediante tecnologías avanzas como sistemas de reconocimiento facial, seguimiento de ojos, sensores biométricos, pulseras de actividad, etc. A esto se le conoce como analítica del aprendizaje multimodal, *Multi Modal Learning Analytics* (MMLA) [2], en terminología inglesa. Esta ampliación de la recolección de datos puede permitir mejorar la predicción, comprensión, motivación y cuantificación del aprendizaje y de los alumnos [2] y es directamente aplicable a plataformas educativas basadas en *IoT y wearables*.

Dentro del enfoque MMLA, el registro de las interacciones de los usuarios en los sistemas educativos permite analizar sus acciones a un nivel muy detallado, así como definir patrones de comportamiento de los alumnos cuando interactúan con las plataformas educativas tecnológicas [42]. Filvá et al. plantean una solución [20] para categorizar y entender los clics que producen los alumnos cuando están utilizando la plataforma de programación Scratch. Detectan patrones en el comportamiento de los alumnos en base a cuántos, con qué frecuencia y en qué zonas de la interfaz de Scratch se producen los clics mientras están desarrollando las tareas que se les plantean. Mediante estos patrones de comportamiento, los autores categorizan a los alumnos en tres tipos. El primer grupo, alumnos bloqueados, no interaccionan o están excesivamente centrados en una zona de la interfaz. El segundo grupo, alumnos que realizan la tarea a un ritmo normal, la sucesión de clics es acorde y lógica a la tarea que están desarrollando. Y por último el tercer grupo, alumnos que desarrollan las tareas por prueba y error, son alumnos que realizan continuos cambios y comprueban constantemente los resultados. Cocea et al. [13] presentan un estudio sobre si es posible determinar el nivel de motivación de los alumnos que utilizan una plataforma online de aprendizaje del leguaje HTML (HyperText Markup Language). Para este estudio se centran en realizar un análisis de datos de los archivos de registro de la plataforma en busca de patrones de comportamiento. Entre los parámetros que analizan destacan el tiempo dedicado a la lectura de los enunciados, tiempo dedicado a responder, número de respuesta correctas e incorrectas, etc. Los resultados del estudio sugieren que el tiempo dedicado a la lectura de los enunciados es un factor importante para medir el nivel de motivación.

En el contexto de esta tesis doctoral es muy relevante el estudio sobre el diseño, evaluación y adecuación de una plataforma educativa *IoT y Wearable* en el que se apliquen un enfoque MMLA. Una plataforma de estas características permite la monitorización continua de los niveles de motivación así como determinar patrones de comportamiento de los alumnos. Los educadores con estos datos podrán establecer estrategias y metodologías que permitan mantener el compromiso de los alumnos con el proceso educativo, lo que influye directamente en reducir los niveles de abandono escolar prematuro.

## 1.2 Objetivos y cuestiones de investigación

Esta tesis se centra en el diseño y desarrollo de una plataforma TIC, basada en las tecnologías *IoT y Wearable*, con el fin de estudiar cómo su uso puede contribuir en reducir los niveles de abandono escolar temprano, a través del nivel de motivación de los alumnos. Por un lado se estudia cómo el uso de estas tecnologías genera intrínsecamente motivación en los alumnos mientras realizan actividades educativas basadas en tareas. Y por otro lado, se estudia cómo estas tecnologías permiten recolectar datos que van a permitir detectar el nivel de motivación de los alumnos a través de patrones de comportamiento.

Después de realizar una rigurosa revisión del estado del arte sobre el objetivo general de esta tesis, se han definitivo los siguientes 3 objetivos y sus correspondientes cuestiones de investigación.

### 1.2.1 Objetivo 1

El primer objetivo que se plantea es el **estudio de los beneficios que el uso de las tecnologías *IoT y Wearable* aportan cuando se utilizan en actividades educativas basadas en tareas**. Para este tipo de actividades el uso de estas tecnologías permite la creación de entornos de aprendizaje amigables y atractivos. También proporcionan a los profesores herramientas de seguimiento y evaluación de los alumnos. Esto es muy beneficioso al liberar a los educadores de tener que mantener registros manuales de las tareas realizadas por cada alumno durante las actividades. En su lugar, los educadores pueden centrar sus esfuerzos en crear un ambiente agradable y animar a los estudiantes a participar.

Para realizar el estudio que plantea este objetivo es necesario la realización de los siguiente sub-objetivos:

- Sub-objetivo 1.1: Diseño y puesta en marcha de una plataforma educativa basada en las tecnologías *IoT y Wearable* en la que los alumnos realicen actividades basadas en tareas.
- Sub-objetivo 1.2: Realizar un estudio de validación de la plataforma a través de su evaluación con los usuarios finales, alumnos y educadores. Es necesario realizar una comparación entre activadas realizadas con la plataforma y sin la plataforma.

En esta tesis, y para este primer objetivo, la plataforma diseñada está centrada en actividades para el aprendizaje de idiomas en niños de educación primaria. El diseño se basa en uno de los principales requisitos educativos en el ámbito del aprendizaje de lenguas extranjeras propuesto por Cameron [10]: "Cuando se comienza el estudio de lenguas extranjeras, los alumnos pequeños necesitan un vocabulario muy específico que se asocie a objetos que puedan ver y manejar". Para evitar tratar ideas abstractas, Cameron recomienda realizar actividades relacionadas con temas que a los alumnos les resulten familiares, como la familia, los amigos, la vida escolar, etc. Como tienen una imagen mental clara de estos objetos y actividades, les resulta más fácil procesar la información en la lengua extranjera. La plataforma transforma el aula en un espacio en el que los alumnos clasifican palabras representadas por objetos inteligentes con los que interactúan para completar un objetivo común. La realización de actividades con la plataforma *IoT y Wearable* genera un registro de datos que pueden analizar. Este análisis debe permitir a los educadores realizar un aprendizaje reflexivo, es decir, que pueden cambiar o modificar las actividades en función de la experiencia que muestran los datos. El diseño de la plataforma *IoT y Wearable* para el estudio se basa en la interacción con objetos inteligentes basados en la tecnología NFC y *smartphones* que hacen la función de dispositivos *wearables*. Además, se incluye la tecnología BLE para dividir tecnológicamente espacios en el aula. Para validar el diseño es necesario realizar una comparación entre actividades realizadas con la plataforma y sin la plataforma.

En este objetivo se plantean las siguientes cuatro cuestiones de investigación (CIs):

- CI1. ¿Puede generarse y mantenerse la motivación de los alumnos en la realización de actividades educativas basadas en el uso de dispositivos *IoT y Wearable*?
- CI2. ¿Las actividades educativas basadas en el uso de dispositivos *IoT y Wearable* mejoran la colaboración y la comunicación entre los alumnos?
- CI3. ¿Las tecnologías *IoT y Wearable* guían con éxito a los alumnos a en las actividades educativas?
- CI4. ¿Mejoran las tecnologías *IoT y Wearable* la calidad del aprendizaje?

### 1.2.2 Objetivo 2

La mayoría de los estudios encontrados en la bibliografía se centran principalmente en el uso educativo de las tecnologías *IoT y Wearable* para una sola actividad en particular, sin considerar su uso en una plataforma educativa global en la que se puedan realizar diferentes actividades de diferentes materias.

En base a los resultados obtenidos, las lecciones aprendidas, y los comentarios de los usuarios finales, el segundo objetivo de esta tesis es **ampliar el diseño de la plataforma *IoT y Wearable*, para poder ser utilizada como una plataforma global de enseñanza**. Para alcanzar este objetivo, se plantean los siguientes sub-objetivos:

- Sub-objetivo 2.1: Ampliar la plataforma *IoT y Wearable* para la realización y el apoyo de actividades de aprendizaje y enseñanza en general.

- Sub-objetivo 2.2: Diseñar un dispositivo *wearable* específico para la interacción en entornos educativos IoT.

La ampliación del diseño de la plataforma tiene que ser validada a partir de la realización de pruebas en diversos escenarios, en términos de eficacia para la enseñanza, usabilidad y satisfacción del usuario. Así mismo, habrá que validar el dispositivo *wearable* en términos de funcionamiento, usabilidad y carga de trabajo generada con respecto al uso de los dispositivos utilizados en el anterior estudio, los *smartphones*.

En este objetivo se plantea la siguiente cuestión de investigación:

- CI5. ¿Puede la plataforma *IoT y Wearable*, potenciar los procesos de aprendizaje y enseñanza hacia una nueva calidad de experiencia de uso?

### 1.2.3 Objetivo 3

El uso de plataformas basadas en las tecnologías *IoT y Wearable* permite recolectar una gran cantidad de datos sobre los que aplicar MMLA. Con el análisis de estos datos y aplicando tanto metodologías MMLA como técnicas de aprendizaje automático, se pueden construir modelos capaces de detectar motivación de los alumnos mientras realizan tareas educativas.

En base a los resultados obtenidos en los objetivos previos y a las lecciones aprendidas, el tercer objetivo de esta tesis es **aplicar metodologías MMLA y técnicas Machine Learning sobre la plataforma *IoT y Wearable* propuesta, en busca de patrones de comportamiento con los que medir la motivación de los alumnos**. Este objetivo se fundamenta en la realización de diferentes experimentos en un contexto de aprendizaje participativo a largo plazo.

Para alcanzar este objetivo se plantean los siguientes sub-objetivos:

- Sub-objetivo 3.1: Creación de una clasificación de patrones de comportamiento de los alumnos mientras interactúan con la plataforma IoT wearable. Esta clasificación se obtiene aplicando MMLA sobre los datos recolectados durante un año escolar.
- Sub-objetivo 3.2: Crear un modelo de reglas que relacione los patrones de comportamiento con el nivel de motivación de los alumnos utilizando métodos de aprendizaje automático. Este modelo proporciona al profesor información para que pueda tomar decisiones en tiempo real, conocer mejor a los alumnos, su comportamiento, su aprendizaje, etc.

En este objetivo se plantea la siguiente cuestión de investigación:

- CI6. ¿Puede la propuesta de plataforma *IoT y Wearable* proporcionar información sobre la motivación de los alumnos utilizando metodologías MMLA?

## 1.3 Metodología y plan de trabajo

La metodología y el plan de trabajo seguido se han organizado en base a la consecución de los tres objetivos principales definidos en el apartado 1.2. A continuación se describe esquemáticamente los trabajos realizados para cumplir con estos objetivos.

1. Estudio de los beneficios que el uso de las tecnologías *IoT y Wearable* proporcionan en la realización de actividades educativas.

    1.1. Revisión exhaustiva de la bibliografía sobre entornos educativos basados en la utilización de TICs y centrados en la mejora de la motivación de los alumnos.

    1.2. En colaboración con educadores, diseño de una plataforma *IoT y Wearable* en la que se puedan realizar actividades educativas basadas en tareas.

    1.3. Validación de la plataforma mediante la evaluación de la misma con usuarios finales.

    1.4. Realización de un análisis de resultados comparando tareas realizadas con la plataforma y sin la plataforma.

2. Ampliación de la plataforma *IoT y Wearable* para poder ser utilizada como una plataforma global de enseñanza.

    2.1. En colaboración con educadores, y en base a las nuevas características determinadas en el objetivo anterior, rediseño de la plataforma para poder ampliar el número de actividades en las que se puede utilizar.

    2.2. Revisión de la bibliografía sobre la utilización de dispositivos *wearables* en contextos educativos para mejorar la motivación de los alumnos.

    2.3. Diseño de un dispositivo *wearable* para la interacción de los alumnos con la plataforma.

    2.4. Validación de la plataforma y del dispositivo *wearable* mediante la evaluación de la misma con usuarios finales.

3. Estudio sobre la aplicación de un enfoque MMLA sobre los datos capturados por la plataforma, para obtener un modelo que determine la motivación de los alumnos.

    3.1. Revisión de la bibliografía sobre el tratamiento de datos mediante la aplicación de técnicas MMLA y ML.

    3.2. Realización de una evaluación a largo plazo durante un curso escolar con un grupo de alumnos de secundaria.

    3.3. Aplicación continua de métodos de análisis exploratorio de datos [40] y de observación directa [39] sobre los datos que son capturados en la evaluación a largo plazo. Con este análisis se obtiene la taxonomía de patrones de comportamiento.

3.4. Generar un modelo que determine la motivación de los alumnos utilizando técnicas de ML.

3.5. Validación del modelo generado con los educadores.

Los trabajos de investigación han estado dirigidos por evaluaciones empíricas. Estas se ha basado en uno de los cuestionarios enfocados en evaluar la usabilidad del sistema, concretamente el SUS (System usability scale) [9], así como en la técnica de observación directa [31]. Para el análisis de los datos, se han utilizado diferentes técnicas estadísticas estandarizadas.

Los diseños, artefactos, métodos y modelos desarrollados han sido evaluados mediante experimentos controlados y casos de estudios con el fin de valorarlos y mejorarlos.

## 1.4 Estructura de la tesis

Esta tesis doctoral se presenta en forma de compendio de artículos, cumpliendo con la estructura indicada en las directrices básicas y comunes establecidas por el Comité de Dirección de la Escuela Internacional de Doctorado de la Universidad de Castilla-La Mancha, fijadas en su reunión del día 7 de junio de 2016. Esta compuesta por cuatro capítulos, (i) Introducción, (ii) Resultados, donde se presentan los artículos que conforman el compendio. (iii) Discusión general y un último, (iv) Conclusiones sobre el trabajo realizado en esta tesis y las Perspectivas de Futuro. A continuación se detalla el contenido de los cuatro capítulos.

- El capítulo 1 presenta los elementos generales de la tesis, se expone la justificación y la motivación por la que se ha realizado esta tesis. Se plantean los cuestiones de investigación y objetivos y se presenta la metodología y plan de trabajo que se ha llevado acabo, y el presente apartado de estructura.
- El capítulo 2 muestra los resultados correspondientes al compendio de artículos por el que se presenta esta tesis, los artículos son presentados en el formato original de las publicaciones correspondientes.
- El capítulo 3 presenta una discusión sobre los resultados obtenidos, donde se expone una amplia discusión sobre la investigación realizada, los objetivos alcanzados y las cuestiones de investigación.
- El capítulo 4 se presentan las conclusiones y las perspectivas de futuro para continuar la línea de investigación de esta tesis.

Capítulo 2

# Resultados

En este capítulo se presentan los principales resultados obtenidos durante esta tesis doctoral y que están mostrados en las publicaciones que conforma el compendio. El capítulo esta dividido en tres secciones que se corresponden con las tres publicaciones, y que dan respuesta a los objetivos y cuestiones de investigación planteados en la sección 1.2.

- El artículo presentado en la sección 2.1, *"Introducing IoT and Wearable Technologies into Task-Based Language Learning for Young Children"*, completa el objetivo 1 y da respuesta a las cuestiones de investigación CI1,CI2,CI3 y CI4.
- El artículo presentado en la sección 2.2, *"WIoTED: An IoT-Based Portable Platform to Support the Learning Process Using Wearable Devices"*, completa el objetivo 2 y da respuesta a la cuestión de investigación CI5.
- El artículo presentado en la sección 2.3, *"Data Capture and Multimodal Learning Analytics Focused on Engagement With a New Wearable IoT Approach"*, completa el objetivo 3 y da respuesta a la cuestión de investigación CI6.

## 2.1 Introducing IoT and Wearable Technologies into Task-Based Language Learning for Young Children

**Publication Data**

**ABSTRACT:**
In the last few years, in an attempt to further motivate students to learn a foreign language, there has been an increasing interest in task-based teaching techniques, which emphasize communication and the practical use of language, thus moving away from the repetitive grammar-translation methods. Within this approach, the significance of situating foreign language learners in scenarios where they can meaningfully learn has become a major priority for many educators. This approach is particularly relevant in the context of teaching foreign languages to young children, who need to be introduced to a new language by means of very concrete vocabulary, which is facilitated by the use of objects that they can handle and see. In this study, we investigate the benefits of using wearable and Internet-of-Things (IoT) technologies in streamlining the creation of such realistic task-based language learning scenarios. We show that the use of these technologies will prove beneficial by freeing the instructors of having to keep records of the tasks performed by each student during the class session. Instead, instructors can focus their efforts on creating a friendly environment and encouraging students to participate. Our study sets up a basis for showing the great benefits of using wearable and IoT technologies in streamlining 1) the creation of realistic scenarios in which young foreign language learners can feel comfortable engaging in chat and becoming better prepared for social interaction in a foreign language, and 2) the acquisition and processing of performance metrics.

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# Introducing IoT and Wearable Technologies into Task-Based Language Learning for Young Children

Elena de la Guía, Vicente López Camacho, Luis Orozco-Barbosa, Víctor M. Brea Luján, Víctor M. R. Penichet, and María Lozano Pérez

**Abstract**—In the last few years, in an attempt to further motivate students to learn a foreign language, there has been an increasing interest in task-based teaching techniques, which emphasize communication and the practical use of language, thus moving away from the repetitive grammar-translation methods. Within this approach, the significance of situating foreign language learners in scenarios where they can meaningfully learn has become a major priority for many educators. This approach is particularly relevant in the context of teaching foreign languages to young children, who need to be introduced to a new language by means of very concrete vocabulary, which is facilitated by the use of objects that they can handle and see. In this study, we investigate the benefits of using wearable and Internet-of-Things (IoT) technologies in streamlining the creation of such realistic task-based language learning scenarios. We show that the use of these technologies will prove beneficial by freeing the instructors of having to keep records of the tasks performed by each student during the class session. Instead, instructors can focus their efforts on creating a friendly environment and encouraging students to participate. Our study sets up a basis for showing the great benefits of using wearable and IoT technologies in streamlining 1) the creation of realistic scenarios in which young foreign language learners can feel comfortable engaging in chat and becoming better prepared for social interaction in a foreign language, and 2) the acquisition and processing of performance metrics.

**Index Terms**—Human-computer interaction, internet-of-things, language learning, sensor data, wearable devices

## 1 Introduction

In the last few years, in an attempt to further motivate students to learn a foreign language, there has been an increasing interest in task-based teaching techniques, which emphasize communication and the practical use of language, thus moving away from the repetitive grammar-translation methods [1]. Within this approach, the significance of situating foreign language learners in scenarios where they can meaningfully learn has become a major priority for many educators. This approach is particularly relevant in the context of teaching foreign languages to young children, who need to be introduced to a new language by means of very concrete vocabulary, which is facilitated by the use of objects that they can handle and see [2]. Towards this end, the interaction through sensor-enabled objects and wearable devices has a great potential to support learning due to hands-on engagement, enabling the collaboration and role to be played by each student. Furthermore, the use of these technologies can minimize the cognitive load in learning, by enhancing the learning and collaboration of children through everyday physical objects, wearable technologies and real-world scenarios. Compared to other techniques, task-based language learning with tangible user interfaces has the potential of enhancing the educational experience and creative problem solving activities bringing students to the next level of learning [2].

In a recent study aiming to get an overall picture of the educational affordances of wearable technologies, Bower and Sturman [3] have reported on the conclusions derived from a survey counting with the participation of more than 300 educators. Their study also comprised a brief review of the latest efforts on the use of wearable technologies in education. All empirical studies cited in [3] were targeted to adults making use of head-mounted displays or Google Glass.

The study highlighted one of the main challenges preventing the widespread use of these technologies in the classroom: a large percentage of educators are neither familiar with these new technologies, nor convinced of the benefits of introducing them into the classroom. Issues such as cost, cognitive overload, privacy, and those of an ethical and social nature were among the main concerns raised by the survey respondents.

Antle and Wise [2] have pointed out that educators should play a major role in guiding the development of hands-on activities that meet the curricula objectives. In turn, developers should be responsible for putting together the elements that make up systems capable of seamlessly integrating the data captured by the wearable and ambient sensors into a valuable source of information for students and educators.

Gilman et al. [4] have analyzed the tools provided by current ubiquitous learning systems for the four main different user roles, namely students, teachers, developers and researchers. Their analysis revealed that current systems mainly satisfy the needs of students, but most current

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systems do not provide teachers with on-line monitoring or analysis tools for student performance. They identified an opportunity for developers and researchers to explore and implement systems based on the real use of devices.

In a recent study [5], Munoz Cristobal et al. introduced a system aimed at helping teachers in the coordination of teaching activities taking place in and outside the classroom. Following the principle that students learn better when they are immersed in real scenarios, the authors developed a system to help the teacher in the multiple aspects of implementing and running educational activities in various educational scenarios. The authors realized that teacher awareness during the outdoor activities is a major issue; this is particularly relevant when working with young children. The use of mobile devices allowed the teachers to be aware of the students' actions during and after the activities.

Tan and So [6] investigated the relationship between activity design and discourse on mobile learning-assisted field trips. Their main findings showed that students' interaction with the physical setting has a profound impact on the way they interpret an activity and their engagement with the activity. They argued that technological tools play a mediating and supporting role in framing mobile learning solutions.

Closely related to the work herein, Hooper et al. reported an IoT-instrumented kitchen for English speakers interested in learning French [7]. The system implemented an augmented kitchen by inserting digital sensors into all the kitchenware and ingredients. In this way, the system is able to detect users' activities and provide timely feedback or more details about a certain cooking action. Users are also able to communicate with the system by using an interactive screen. Each task was designed to teach specific vocabulary and grammar structures. Unlike our proposal, theirs was exclusively centered on a kitchen scenario and for an adult audience interested in culinary activities.

Muller et al. [8] introduced an approach based on wearable and IoT technologies to record context from the workplace and to visualize the data as content for reflective learning. They developed and tested a system prototype for the process of training caregivers and rescuers. Due to the nature of their activity, the correct action at a given point in time can only result from their previous experience. The use of wearable and IoT technology enabled the recording of their behavior while performing their work as well as the acquisition of an overall picture of the general organizational issues. The authors acknowledge the benefits that IoT and wearable technologies may bring by enabling the recording and review of data as reflective contents. However, they recognize that a reflection session has to be carefully planned in order to get the most from the data captured by the technology. Such studies encouraged us to develop IoT and wearable technologies for teaching environments.

The main objective of the work herein is to show that the use of wearable and IoT technologies can greatly contribute to the needs of task-based language learning for young children. As pointed out by recent studies, IoT/wearable teaching tools should not only enable the creation of friendly and engaging task-based learning environments, but they should also provide teachers with on-line monitoring and student evaluation tools. To guide our work, we therefore focus on the following four main research questions:

RQ1. Can students' engagement be generated and maintained through the use of IoT/wearable assisted task-based environments?

RQ2. Do IoT/wearable-enabled learning scenarios enhance collaboration and communication among students?

RQ3. Do IoT and wearable technologies successfully guide the students through the tasks?

RQ4. Do IoT/wearable technologies improve the quality of learning?

We start by designing and setting-up a platform capable of transforming the classroom into a space where young children are given the opportunity to sort out words involving concrete objects and to interact while performing a task leading to a common goal. This addresses one of the main educational requirements in the field of foreign language learning for young children, or in Coffman's own words [9]: "When introduced into the foreign language classroom, young children need very concrete vocabulary that connects with objects they can handle or see". That is to say, in order to avoid dealing with abstract ideas, Cameron [1] recommends dealing with topics that children find familiar, such as family and friends or school life. Since they have a clear mental image of these objects or activities, it is easier for them to process the information in the foreign language.

We also report our findings on the real and tangible benefits for the instructors that are provided by the use of wearable and IoT technologies. In fact, similar to the work in [9], our results show that wearable and IoT technologies may play an invaluable role in recording the context from the classroom. Instructors may then analyze the data as content for reflective learning. That is to say, instructors may change or modify the teaching activities based on their past experience.

## 2 The Task-Based Learning Classroom

This section briefly describes the organization and management of a classroom, as well as the introduction of wearables and IoT technologies into the classroom.

### 2.1 Classroom Management and Organization

It is well known that the classroom environment is influenced by the guidelines established for its operation, its users, and physical elements [10]. In the particular case of task-based language learning involving young children, the organization of the classroom involves the arrangement of tables, chairs and, more importantly, the organization of special designated areas. Since students will be doing different things in the classroom, it is important to designate specific areas in order to optimize learning and reduce distractions. Furthermore, the organization of the classroom has to be carried out by taking into account the type of interactions between the students. Activities may be performed individually, in pairs or in groups. In this way, children learn to associate scenarios with words, objects, and more importantly through interactions with their peers under the supervision of the instructor. In a given scenario, an object may be associated with a real-world environment that allows the children to perform the tasks related to it. For instance, a group of students will share the responsibility for finding the various ingredients required to proceed with the task of preparing dinner. While some children will have to go shopping, following the instructions provided via remotely activated signals, others will be in charge of finding the appliances and kitchenware to lay the table. In this case, the teacher will have to designate two sectors: one sector will be designated as the market, while the second sector should represent the cupboard. A third sector should be identified as the kitchen, where all the students will meet in order to prepare the recipe. From the above, it is clear that the classroom should be divided into sectors and provisioned with the required resources to foster the types of interactions that may occur between participants, including individual, pair and group work. From now on, we will refer to those sectors where interactions occur individually or in pairs as context sectors, and group sectors will be the term used to refer to those sectors where the interactions involve the whole group.

The planning of a task-based lesson such as the one described above does not only require the preparation of material and organization of the classroom, but also the setting of reasonable expectations for students' behavior. Monitoring the class and adjusting lessons accordingly are two important elements in the successful implementation of a task-based learning approach [1]. Providing timely feedback on the goals will help to meet the teaching goals. The students can see that while they are still not able to complete some classroom tasks with the same ease as other students, progress is still being made.

Teachers should be able to monitor these goals and adjust lessons to make sure that all of the students are progressing adequately. In order to be able to make an accurate evaluation of the adequacy of the task as well as the level of participation of each student, the teacher has to keep a record of the key performance parameters of the task session. In fact, record keeping is seen as an area where the use of IoT and wearable technologies should prove invaluable.

### 2.2 Introducing IoT/Wearables into the Classroom

One of the main objectives of our study is to show that the use of sensor-based objects and wearable devices enabling the creation of realistic scenarios should prove invaluable in classroom task processes. As pointed out in [11], nowadays a large number of language teachers express great interest in task-based language teaching, but they do not know where to start. The use of sensor-activated objects and wearable devices should provide them with the tools to create and manage task-based scenarios including everyday objects and friendly interfaces. Via a simple interface, instructors should be able to set up a scenario including sensor-based objects and wearable devices. The former should address one of the main challenges of teaching a foreign language effectively to young children: the need to be introduced to a foreign language using a very concrete vocabulary that connects with objects they can handle or see [1].

As for the use of wearable devices, they provide instructors with the means to follow up on the interactions being performed by each and every student during the task. Data associated to statistics, such as the number of interactions having been performed correctly at a first attempt, the number of attempts required to complete an interaction, the time required to complete a given interaction, and the number of times a student has required further assistance from the instructor, can easily be collected,

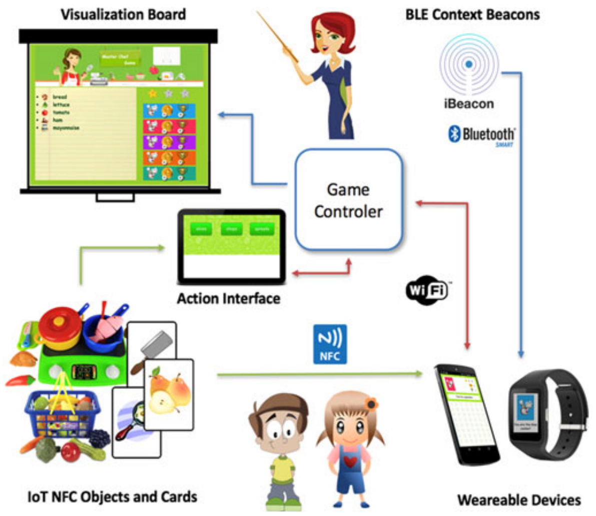



Fig. 1. System components.

processed and visualized. The post-processing of the data captured during a given task can provide the instructor with relevant information on the progress of each and every student. Such information is highly relevant to the day-to-day follow-up and final evaluation [8].

The use of IoT/wearable technologies should also prove of great help in preventing a child from being left behind or from dominating in a given task. It is therefore necessary for each child to be provided with a wearable device that uniquely identifies its owner. However, the choice of the wearable devices to be used requires a clear understanding of the actions composing the task as well as the learning goals. Wearable and IoT devices should be seen as the building blocks of novel intuitive interaction technologies. Furthermore, the execution of each action should be followed by the proper feedback message. This will encourage the student to proceed till the successful completion of the task.

## 3 System Architecture and Implementation

This section describes how we deploy the different objects within the scenario, then we give a simple example of a common task that is frequently performed, and lastly the scenario itself is described.

### 3.1 IoT and Wearable Technologies

Figs. 1 and 2 depict the main elements of the proposed solution and the organization of the classroom into sectors, respectively. The organization of the classroom into sectors is based on: 1) context sectors, where the students have to identify the objects from a list; and 2) a group sector, where the teacher will be coordinating the activities involving all the students using the items collected in the context sectors. The characteristics and operations of the main system elements depicted in Fig. 1 are:

The *Game Controller* is the core of the system. It is composed of a server whose main function is to coordinate the execution of the task, which it does by exchanging data and control messages with wearables using the WiFi network. It

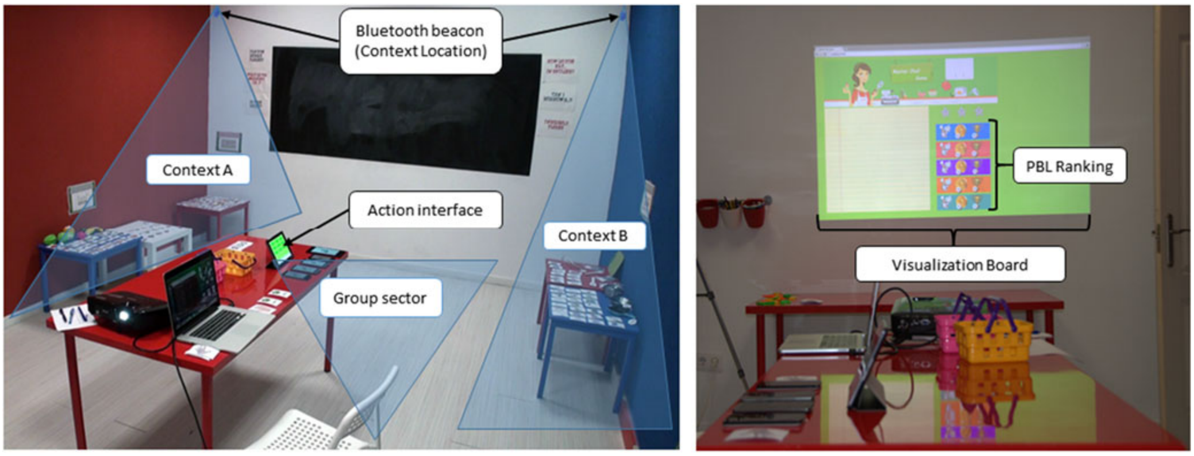



Fig. 2. Organization of the classroom.

is also in charge of displaying information regarding the progress of the task on the Visualization Board and of keeping track of the location of the wearables using the data reported by the Bluetooth nodes (iBeacons).

*WiFi and Bluetooth Communications.* The WiFi connection conveys the outcome of the action being performed to the central game controller. The Bluetooth interface provides the means of identifying, via the wearable device, the location of each wearable (child) within the classroom.

*Bluetooth beacons* are used to estimate the location of the students. Depending on the student's location, the information provided by the beacon is used to guide the students around the classroom. For instance, if a student currently located in Context A is asked for an item found in Context B, the system lets them know that they have to proceed to the appropriate sector.

*Visualization Board.* This is used to display and play the outcome in response to the interactions being performed by the students during the session. The screen is also used to display information regarding the status of the task, such as the objectives achieved and the points awarded to each student.

*IoT objects and cards.* The children have at their disposal a collection of IoT objects. Each object should have been previously marked using an NFC tag. Furthermore, each child should be provided with an NFC-activated id card. The number and types of objects used in a given class session should be determined on the basis of the scenario, the level of complexity of the task to be carried out and the main learning goals. For instance, if the subject matter is preparing a recipe, the IoT objects may consist of food products and kitchenware items. However, the teacher may choose to use a larger number of items than the ones required to prepare a given recipe with the main purpose of challenging the students to identify a given item from among a large number of objects. Depending on the resources available and the scenario, the types of objects used may range from real items to picture cards.

*Action Interface.* This system element consists of a tablet whose operation is supervised by the teacher. It is used in those activities involving the participation of the whole group.

*Wearable devices.* When deciding on the type and features of the wearable devices to be used in the classroom, the designers have to have a clear understanding of the learning methodologies employed by the teachers. In the case of a task-based language learning approach for young kids, students are asked to identify concrete objects by their names and to interact with other students and the teacher by sharing or conducting a task involving objects. As already pointed out, the use of wearable devices should help to focus on the interactions to be performed and to keep track of the interactions performed. For the purpose of our study, the use of a wearable device, such as a smart watch or a smart phone equipped with an NFC reader, and Wi-Fi and Bluetooth interfaces should meet the requirements of a task-based language learning setup for young children. Our design choice can be justified by taking a closer look at a typical task-based language class session. We start by distinguishing between two major interaction modes: one in which a given student will be required to identify an object in reply to a request; and a second mode under which the students will be asked to participate in an activity involving other members of the group. A task-based class session can therefore be thought of as taking place in two major modes. The first one comprises those activities performed in a Context Sector, where students will be mainly asked to find one or more objects. The second one defines the activities performed in the Group Sector, whose main goal is to promote interaction among the students. It is worth mentioning that during a given class session, it is possible that only one or both operation modes take place.

The above organization sets the basis for defining the features and utilization of the wearable devices. It also allows us to specify the interface between the students and the system. When working in a context sector, students will be asked to find one or more objects. When an object is found, the student uses his/her wearable device to scan the IoT object via the embedded NFC reader. For instance, if the student is asked to look for a banana, he/she should simply find the object and scan it. In response to the student's

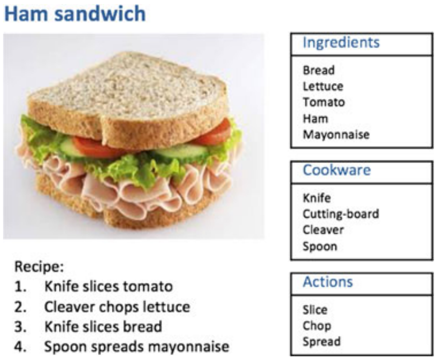



Fig. 3. Description of a sample scenario.

action, a message will be displayed and played on the Visualization Board. In the case of the object not corresponding to the one being asked for, the student will be asked to try again. On the contrary, if the student has picked the right object, a cheering message will be issued. All feedback messages provided to the student will be delivered through the Visualization Board and speakers.

When the students gather together with the teacher in the Group Sector, the teacher will be in charge of coordinating the actions to be performed in order to complete the task. The teacher will assign turns to the students and encourage collaboration among them. In this sector, the students will have to interact with the system via the group action interface and the Visualization Board. In other words, the kids will have to pay attention to the teacher's instructions, and then they will have to interact with the system via the interaction interface. This arrangement offers three major advantages over traditional task-based learning activities: 1) the IoT and wearable devices help to keep track of the steps that have been successfully completed; 2) teachers are relieved of the task of manually keeping a record of the level of participation of each kid; and 3) kids are more likely to follow the instructions provided by the instructor and the system. In other words, teachers should be able to focus more on guiding and encouraging the students rather than having to worry about keeping records and constantly tell them off.

### 3.2 A Sample IoT/Wearable Assisted Task

Before proceeding to describe the system design and implementation, in this section we first describe a typical task-based language-learning scenario. We point out, where necessary, how the IoT and wearable technologies may help to improve classroom activities.

Let us assume that the teacher has defined a task whose ultimate goal is to prepare a recipe. The recipe consists of a list of ingredients and cookware utensils, as well as a procedure, and a list of interactions to be performed (see Fig. 3). The task has been organized into two main parts: one to be carried out in the context sectors and the other one in the group sector.

Before the start of the class, the teacher organizes the classroom into one or more context sectors and one group sector. The number and nature of the context sectors will depend on the task. The IoT objects belonging to a given context will be placed within the same sector (see Fig. 4).

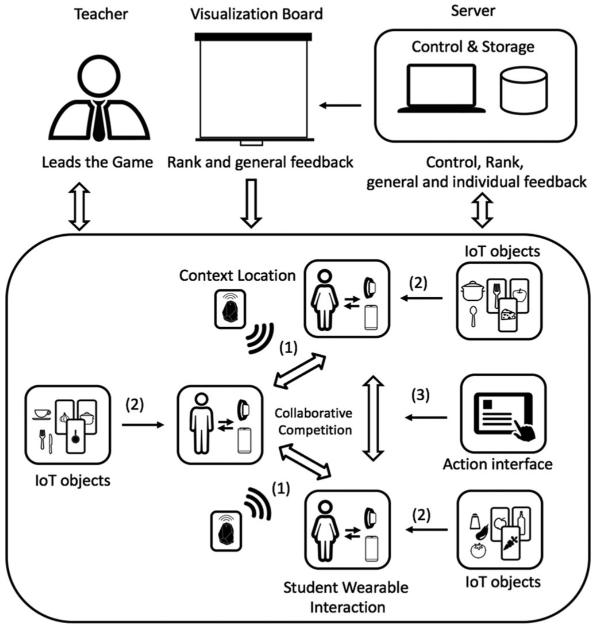



Fig. 4. System operation.

Each sector is identified by an iBeacon, whose main function is to determine the location of the wearables. In this way, the system is able to keep track of, and guide, the students around the different context sectors.

During the first part of the session, the students will have to look for the ingredients and the kitchen utensils. In this scenario, they will have to go to the sector representing *The Market* to look for each recipe ingredient and to *The Cupboard*, to look for the kitchen utensils. For each item in the list, they will have to look for, pick up and scan it using the NFC interface of the wearable devices. As already mentioned, students receive immediate feedback after each interaction. A cheering message is displayed and played for every right answer. In the case of the object not corresponding to the one in the list, or if it has already been found, a feedback message encouraging the student to try again or letting them know that the interaction has already been performed is issued. All the kids can follow the status of the task as it proceeds by consulting the Visualization Board. Once again, a student is allowed to carry out a given interaction only if they are in the right context sector. For instance, if a student has been sent to look for an ingredient, they will be directed to the sector where the ingredients can be found. If they enter another sector, a warning message is sent to them indicating that they should go to the corresponding sector.

For instance, in order to slice the tomato, which is Step 1 of the recipe (see Fig. 3), the student simply has to scan both objects and then point to the corresponding verb, 'slice' in this case, on the screen of the action interface. In order to encourage social interaction and the participation of all students, the teacher will indicate who will be in charge of performing the actions. Furthermore, the instructor may also invite other students to become involved by asking them, for instance, to pass the target object to the child in charge of performing the action. Each student actively involved in the current step will also have to reply. The kid will have to ask for it and both the lender and the borrower will have to scan the object using their wearables and point to the verb on the screen of the action interface. All interactions are logged by the system, including the teacher's request. Finally, the student in charge of slicing the tomato will scan the two objects using the group interface. Then the child will have to point to the verb displayed on the tablet's screen and state that he/she has sliced the tomato: "I sliced the tomato with the knife".

The corresponding feedback is then displayed and played, via the Visualization Board. All the oral exchanges during this activity will be recorded by the system using the wearable devices. The interactions may have to be repeated in the case of the object manipulated not corresponding to the one being asked for, or if the child has been unable to choose the right verb or if the instructor is not satisfied with the students' performance. Furthermore, all the interaction outcomes, whether wrong or right, are automatically logged by the system. The teacher may then review them after the class.

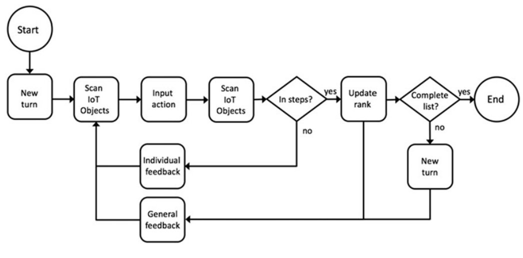
### 3.3 System Operation and Implementation

Bearing in mind that the main objective of our study is to design and evaluate the benefits of using IoT/Wearables in the deployment of a language learning system, we should focus here on the design decisions concerning the interfaces and feedback provided to the students. One of the major design challenges is to design natural and non-invasive interfaces. This is particularly important when developing a system to be used by a group of young kids. It is also important to provide adequate feedback to the kids in order to keep their attention and engagement till the completion of the tasks. To this end, the system implements a Points, Badges, and Leaderboards (PBL) score scheme. Students are awarded points for each interaction that is correctly performed.

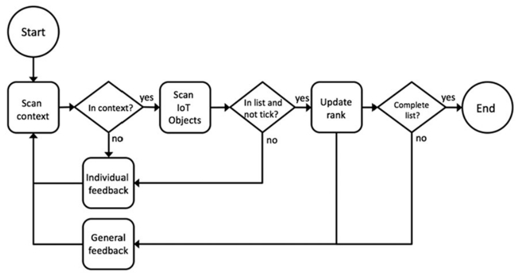
Fig. 4 depicts the system operation. As shown in the figure, the teacher leads the task. The server controls the execution of the task by collecting and processing all the data collected during the class session, following the script prepared by the teacher. The Bluetooth beacons, named Context Location (1) in the figure, determine the position of the students. When they are in a context sector, the students use their wearable devices to interact with the IoT objects (2), and when in the group sector, they use both the wearable devices and the action interface (3).

Following the description of a typical task-based class such as the one described above, we can identify the following user/system interactions:

- Student-Wearable: visual and oral via the screen, the microphone and the speaker. The feedback messages are generated by the server in response to an interaction, for instance, the scanning of an object.
- Student-Wearable-IoT objects: students scan the objects via the NFC reader embedded in the wearable. The wearable object sends information to the server.
- Visualization Board: visual and oral, addressed to the group. The display shows the PBL score, object lists and the steps required to complete a collaborative task. It also shows messages which are usually accompanied by positive feedback sounds.
- Bluetooth: interaction between the Bluetooth beacons and the wearable devices to guide the students around the classroom. The beacons periodically broadcast guiding messages within the range of a context sector.
- Action interface: This interface is used during the activities performed in the group sector. The students, under the guidance of the teacher, are asked to collaborate through the manipulation of the IoT objects.




(a) Context Sector




(b) Group Sector

Fig. 5. Interaction process for (a) Context sector and (b) Group sector.

The system generates two types of feedback messages:

- General feedback: addressed to all students. They consist of both visual and audio cheering or try-again messages. They are conveyed via the Visualization Board and the wearable of the student having performed the interaction.
- Individual feedback: sent only to the student via the wearable device. They are generated whenever the system detects that a student is not in the right sector.

Fig. 5(a) and (b) depict the flowcharts of the interactions that take place in the context sector and the group sector, respectively. In both cases, the students have to scan the objects in order to accomplish the tasks. They receive positive or negative feedback depending on whether they have, or have not, picked the right object, respectively. The system also updates the Visualization Board, showing the points awarded to the student.

Regarding the implementation details, the system has been configured as a client/server. We have developed the system running on the server and the wearable devices using HTML5, Javascript, Web sockets, and Node.js. Taking into account that our solution should accommodate a wide spectrum of wearable devices, we decided to make use of


Fig. 6. Students looking for the recipe ingredients.

HTML5. Being a standard, HTML5 guarantees the portability of the application to practically all types of wearable devices on the market. As for the interconnection technology, we decided to use Websockets. This technology implements a full-duplex communication channel per client via a TCP socket. These features guarantee the reliability and time requirements of the application. Students should receive proper feedback as soon as they scan an object.

## 4 Evaluation

In this section, we present the results obtained during a set of trials conducted in a real language academy in the city of Albacete, Spain. The main objective of the evaluation is twofold: 1) to show that the use of IoT and wearable technologies provides the means to automatically capture relevant information on the progress of a class session, and 2) to evaluate the impact of these technologies on the learning process.

The first goal will help to identify metrics such as the number of times a student attempts to perform a task, the number of right and wrong answers, and periods of high/low participation per student. All these metrics provide useful information on the execution of the class session. Based on their analysis, the teachers can identify the strengths and weaknesses of a given task and/or identify those students requiring further assistance. However, these metrics do not provide us with much information on the impact of these technologies on the learning process. Issues, such as whether the use of wearable technologies could distract students, and the impact on the quality of learning, cannot be completely captured by these metrics. In order to address the second objective, we decided to film the class sessions using a fixed camera and a mobile camera. We have limited our analysis to the four major research questions (RQ) posed in the introduction section.

### 4.1 Experimental Setup and Methodology

Fifteen young children participated in our trials. They were all able to follow simple instructions and to participate in a simple conversation in English. In order to evaluate the impact and benefits of using IoT/wearable technologies in the teaching process, we conducted the same activity using flashcards (paper-based task). Accordingly, we organized the children into three groups. Two groups, namely Groups A and B, participated in the IoT/wearable task-based class activities, while Group C carried out the same activities using the flashcards. We fixed the number of participants involved in our trials following the recommendations in [12], [13], which state that more than 90 percent of usability and user experience issues can be detected with five participants. Their ages range from five to ten years, with a mean of 7.33 and standard deviation of 1.885. They did not have previous experience of using the system, but they all often play games using mobile devices and computers: 43 percent of them play regularly and 57 percent play occasionally. As for Group C, they have some previous experience of using flashcards, but not in the context of an English class activity.

The tasks in our trials consisted in preparing various recipes. Similarly to the recipe explained above, each recipe in our trials consisted of two parts. As shown in Fig. 2, prior to the beginning of the class, the classroom was organized into two context sectors (the Market and the Cupboard) and a group sector. During the first part, the students had to look for the items required to prepare the recipe. They first had to look for the ingredients and then for the kitchen utensils (see Fig. 6). During the first phase, the students were free to proceed, i.e., they were not assigned turns. They just had to collaborate and organize themselves to find all the items required to prepare the recipe. During the second phase of the task, the students had to collaborate, in the group sector, and prepare the recipe under the teacher's supervision. In this case, the teacher assigned turns to the students.

Fig. 2 shows the organization of the classroom. The market place consisted of 85 items: 75 picture cards and 10 objects. The cupboard consisted of forty IoT items: 30 cards and 10 objects. All the items carried an NFC tag. In the group sector, the students had to complete a total of 15 steps involving the use of two objects and an action (verb). Table 1 shows the list of recipes used in the experiment.

During our trails, the students used five smartphones equipped with NFC, Wi-Fi and Bluetooth interfaces. The action interface was implemented on a tablet. All the mobile devices ran under Android. Each IoT object was identified using a 13.56 MHz NTAG 213 and a memory capacity of 144 Bytes. The Visualization Board was implemented using a projector. The server was implemented on a laptop equipped with speakers (see Fig. 2).

Table 1
Session Recipes

| Recipe | Task | Ingredients | Cookware | Actions | Steps |
|---|---|---|---|---|---|
| Ham sandwich | 0 | 5 | 4 | 3 | 4 |
| Fruit and pasta salad | 1 | 11 | 6 | 9 | 7 |
| Vegetables cake | 2 | 11 | 6 | 10 | 10 |

Our original plans were to provide each kid with a smartwatch. However, at the time of initiating the project, we were unable to obtain a fully operational application on a smartwatch. For this reason, we decided to use smartphones instead. We believe that our findings should not deviate from those expected when using smart-watches. In fact, one of our main goals was to design a set of simple interactions in order to reduce the negative impact due to distractions. Furthermore, our system has been designed by taking into account that teachers need to know what the students are actually doing [9].

At the beginning of the class, the teacher explained to the kids the principles of operation of the system and the details of the activities. During the first part of the task, the teacher only assisted the students while they were looking for the required items. During the second part of the task, namely preparation of the recipe, the teacher assigned turns to the students. As for Group C, the kids made use of flashcards. In this case, the teacher had to lead all the actions, check that all the actions had been completed, keep a record of the performance of each student and provide proper feedback.

In order to obtain data on engagement, motivation, verbal sentences, and emotions while performing the tasks, two video cameras were used during the sessions. The purpose of this direct observation method, widely used by the Human Computer Interaction community, is to collect information allowing the evaluator to assess the subjects without altering their environment [14].

At the end of the sessions with groups A and B, the students filled in a survey based on the Smileyometer scale [15]. Based on their experience, they had to choose one of the five pictorial representations, ranging from awful to brilliant, to express their opinion on the activity. They were also given a simplified version for children of the IMI survey consisting of two questions: (1) have you enjoyed playing?; and (2) would you play again? [16]. Two members of our research team analyzed the videos taken during the class sessions in order to evaluate the intrinsic motivation, extrinsic motivation, attention focused on the concepts or on the devices and level of collaboration, verbal interaction and communication among the children.

### 4.2 Results

In this section, we first review the main benefits in terms of the information that can be obtained from the data captured using the wearables and IoT devices. Metrics such as the number of right vs. wrong answers, and the level of participation of each student can be obtained from the data captured though the wearables and IoT objects. This invaluable source of information can be used to review the adequacy of the tasks on the basis of the performance of each student or the group as a whole.

Figs. 7 and 8 show the statistics for each student and both groups, A and B, during the class sessions, respectively. The class session with group A consisted of two tasks, Task 1 and Task 2, while group B completed three

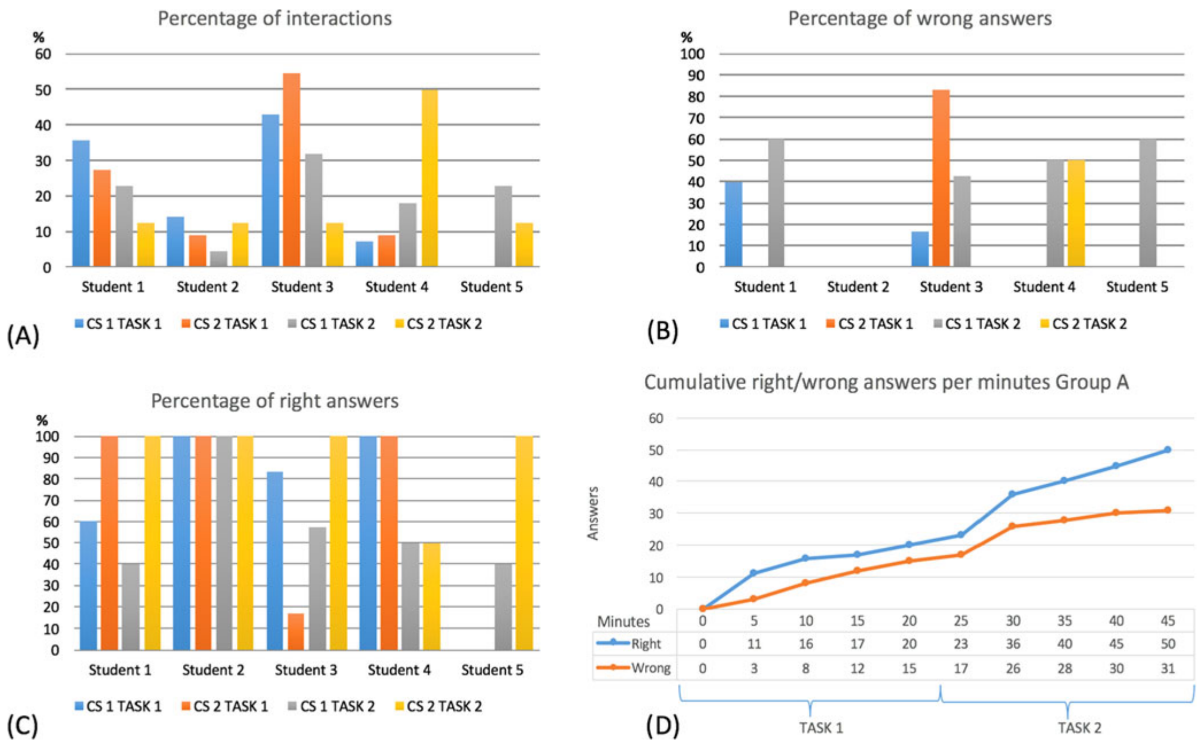


Fig. 7. Task statistics.

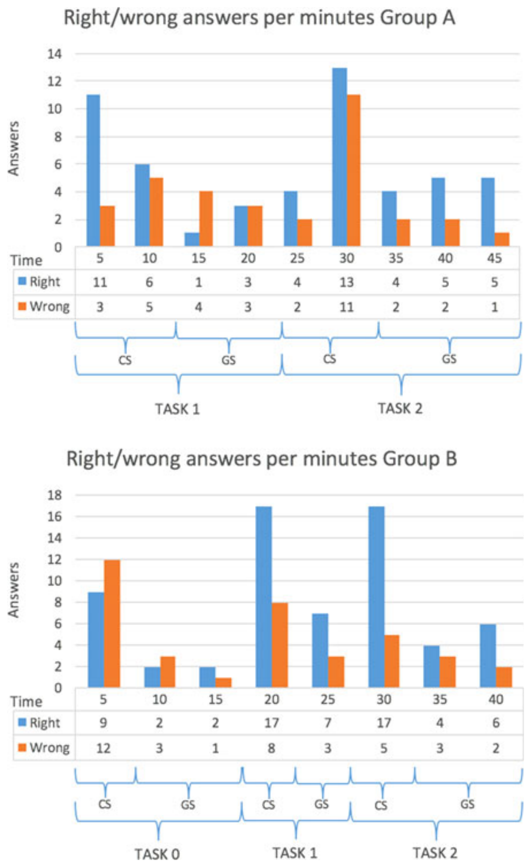



Fig. 8. Right/wrong answers.

tasks. All these tasks consisted in the preparation of a recipe. For the sake of clarity, in the figures we denote by CS the activities performed in the context sector, in which the students had the freedom to look for the recipe ingredients individually, i.e., they were not forced to collaborate. In turn, GS refers to the activities performed in the group sector, where the teacher asks the students to collaborate in the recipe preparation. In order to obtain a better insight into the kind of information a teacher may derive from the data collected by the interactions between the IoT and wearable devices, we report the statistics in periods of approximately five minutes.

In the case of group A, the results show that during the first five minutes of task 1 (recipe 1), the number of right answers was very high, i.e., students made very few mistakes. During the following five minutes, the number of right answers was slightly higher than that of wrong answers. If we take a closer look at the results for task 2, the number of wrong answers experienced a big increase while the number of right answers remained practically unchanged. This unexpected result can be explained by taking a closer look at the level of participation of each kid in the group. Fig. 7(a), (b) and (c) show the percentage of interactions, and right and wrong answers per student during the CS phase for each of the tasks (recipes). Fig. 7(a) shows that during the first five minutes of task 1, two students, namely students 1 and 3, performed most of the interactions. It also shows that student 5 did not participate at all. However, during the second task, student 5 obtained excellent results while the level of participation of students 1 and 3 dropped significantly. In fact, this information was confirmed by analysis of the video taken during the class session. The video revealed that during the first task, students 4 and 5 had problems integrating into the group, while during the second task students 1 and 3 assisted them. This clearly shows that the use of wearables and IoT objects sets the basis for the development of an invaluable monitoring tool. Based on the data captured during the class session, the instructor may change the scheduling of the activities on the fly, or he may plan them differently by following the input from the data provided by the wireless devices. In fact, Muller et al. have recently pointed out the benefits of using the data recorded by the IoT and wearable technologies as reflective contents [8]. Our results confirm the great potential of IoT/wearable assisted task-based teaching tools.

Fig. 8 shows the results for group B. By comparing the results obtained for both groups, the results show that group B had more difficulties during the first five minutes of task 0, while both groups obtained similar results during the GS phases of all tasks. This can be explained by the fact that the complexity of this phase is a little higher. The students first had to pick two items, scan them using the tablet, and then choose the verb by pointing on the screen of the tablet. Based on the information obtained from the data captured by the system, the teacher can reorganize the class. For instance, he may decide to change the rules of the task with the aim of improving collaboration among the students, or decide to place students exhibiting better language skills into another class.

In order to further assess the benefits of the system for the learning process, we now proceed to review the results obtained from the analysis of the surveys conducted after the sessions, and the analysis of the videos recorded during the class sessions.

The videos are an important source of information that allows us to assess the benefits of using IoT and wearable technologies. We focus our attention on obtaining answers to the four aforementioned research questions. In the following, we present the methodology and results obtained for each of the four key questions.

*RQ1. Can students' engagement be generated and maintained through the use of IoT/wearable assisted task-based environments?*

With regard to the children's motivation, two sources of information were considered: the results from the survey and those from classroom observations.

Recent field experiments have shown that intrinsic motivation produces deeper engagement in learning activities, better conceptual learning, and higher persistence at learning activities [17]. Taking into account the benefits that have intrinsic motivation in learning, we analyzed both the intrinsic and extrinsic motivation to determine the children's engagement while performing the learning tasks in IoT environments using wearables and IoT technologies.

Intrinsic motivation is based on enjoyment or interest. In this case, and in accordance with [18], we chose the following factors/indicators: curiosity (CU), explorer (E), collaboration (CL), challenge, and control (CN). Extrinsic motivation is based on external rewards or avoiding

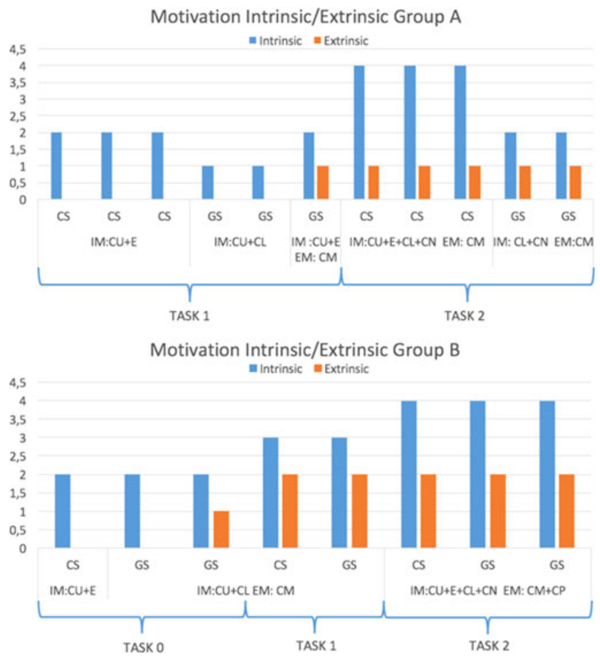



Fig. 9. Intrinsic/extrinsic motivation.

negative consequences. The factors for measuring the extrinsic motivation are points (P), rewards (R), competitiveness (CP), and the comments from the teacher and classmates (CM). Each factor adds a point, which indicates the number of factors (both intrinsic and extrinsic motivation) observed while performing the tasks.

After analyzing the video, we witnessed that in the first class sessions for both groups, when conducting actions in the context sectors, factors for intrinsic motivation such as curiosity and exploration (CU + E) were triggered. In the following sessions, children took control of some of the activities. In fact, they felt more confident in engaging in a simple conversation while picking up the objects at the *Market* or the *Cupboard*. During the group activity, the kids followed the instructions provided by the system by waiting for their turn. This facilitated the task of the teacher, who was able to follow the level of participation of each child, while the system enabled the automatic recording of each action performed by the kids. However, there is room for improving the design of this activity. In particular, the inclusion of actions involving more than one student could help with improving the social interaction among the participants while reducing the waiting time for their turns.

The results showed that the intrinsic motivation prevails above the extrinsic motivation. They find exploring a real environment more attractive and interesting, and it allows them to collaborate and improve the verbal communication with their classmates. However, while working with the tablet in the group sector (GS), some children became distracted while waiting for their turn. Furthermore, the limited size of the tablet screen offered reduced visibility for some children.

The enjoyment (Smileyometer) test results were as follows: 100 percent of the children thought that the games were “brilliant”. None of them thought that the games were awful, really good or not very good. Our results suggest that the children were highly motivated to play IoT learning games, even at the end of the classroom session (see Fig. 9). After analyzing the results, we notice that the system increases the engagement of children because intrinsic motivation dominates over extrinsic motivation. Regarding the technological tools, the children are more easily motivated in IoT environments and with wearables than playing around a tablet.

As for Group C, the results show that the extrinsic motivation prevails. At the beginning of the session, they paid attention to the instructions provided by the teacher. However, the kids quickly started to compete for the objects and the attention of the teacher. Some kids even leaned over the table edge in an attempt to get a card. In turn, the teacher had a hard time keeping a record of the actions being performed and providing accurate feedback on an individual basis. In fact, some kids misinterpreted the feedback provided by the instructor or felt that they were not given the right credit for a given action. When asked to fill in the Smileyometer, two of the kids expressed that they did not like the activity at all.

*RQ2. Do IoT/wearable-enabled learning scenarios enhance collaboration and communication among students?*

Collaborative learning is an important team process, playing a major role in language learning. The classroom is an excellent place to develop social and communication skills, and to improve decision-making, engagement and knowledge acquisition.

In order to evaluate the level of collaboration among the students, besides the information provided by the data captured through the IoT and wearable devices, we analyzed the video material. We count the number of interactions with the system and their peers. The results show that at the beginning of the session, the children displayed little interaction (see Fig. 10). As they became more confident with the technology and the content of the task, they started to collaborate and help their peers. We noticed a significant difference between the two groups. During the process of getting the objects, Group B was less likely than Group A to engage in a collaboration. As for the second phase, when the students had to prepare the recipe, they helped each other to find the objects, but they were less cooperative when it came to interacting with the tablet. The teacher had to assign turns in order to accommodate everyone.

In the case of Group C, the kids showed little interest in collaborating. They had a hard time keeping focused on the task while waiting for their turn, and some of them even walked away from the table. At times, the teacher had to tell some kids off, making it impossible for her to keep a record of the progress made by the students.

*RQ3. Do wearable and IoT technologies successfully guide the students through the tasks?*

From our analysis of the video material, we notice that during the first part of the first task, namely the CS phase, the children paid more attention to the wearables (see Fig. 11). This can be explained by the fact that they needed to become familiar with the system interface. However, as they became acquainted with the system, they focused their attention on the objects (content to be learned), the recipe (Visualization Board) and started helping their peers.

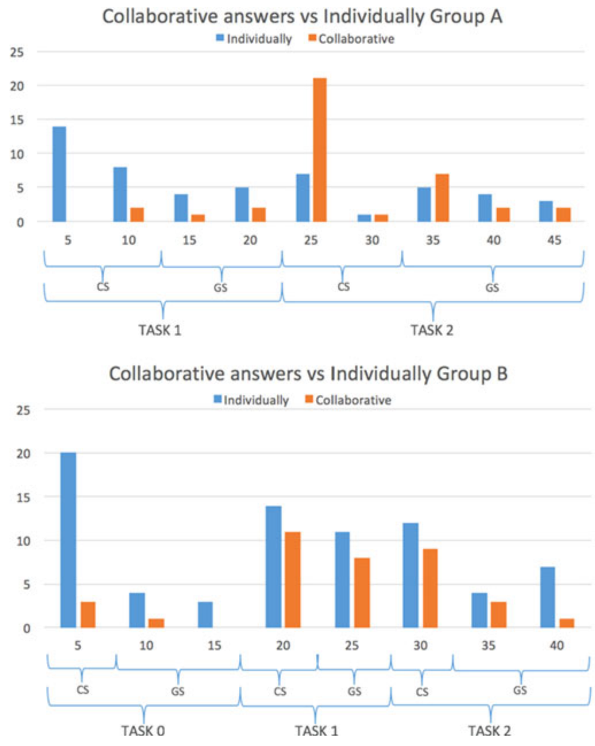



Fig. 10. Collaboration.

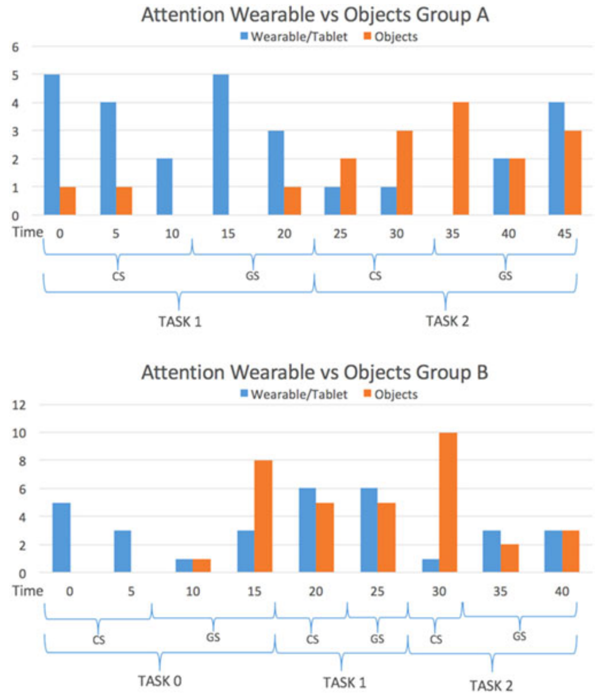



Fig. 11. Attention.

As for the results for the GS phase of the tasks, we notice that the students collaborate while looking for the items, focusing mainly on the objects. Since they had to interact with the tablet in order to point to the verb connecting the two objects, our results show that the students pay equal attention to the objects and to the tablet. However, looking back at the results shown in Fig. 7, we notice that the students have made proper use of the tablet by reducing the number of mistakes made during the GS phase of task 2.

In the case of Group C, the kids focused mainly on the objects. After a while, they showed little interest in collaborating, interacting with their classmates or following the teacher's instructions. In turn, the teacher had a hard time to keep the attention of some of the students while recording the actions being performed.

*RQ4. Do IoT/wearable technologies improve the quality of learning?*

In order to obtain an insight into the impact of the use of the technologies on the learning process, we should look at the progress made by the students throughout the classroom sessions. Fig. 8 shows that by the end of the session, which was task 2 for group A and task 3 for group B, the students obtained better results: the number of wrong answers significantly decreased by the end of the sessions for both groups. This is an excellent result taking into account that the class session lasted almost an hour. From a pedagogical point-of-view, the results show the effectiveness of interleaving periods of group work with fun (play) activities. Through the use of IoT and wearable technologies, we have been able to get the most out of the fun period. While looking for the items, the students learn new vocabulary. Each interaction during this period is recorded, thus making it possible to keep track of the level of participation of each kid. In an attempt to assess the effectiveness of the learning process, two weeks later the kids were asked to take a test. The results showed that the students in group A and B remembered 85 percent of the more unfamiliar words and more than half of the verbs; while the results for Group C revealed that some students had a very hard time remembering more than half of the more familiar nouns, and almost none of the verbs.

From the post-test phase (simplified IMI survey), the following results were obtained. In response to the questions, 100 percent of the children perceived the game as innovative and exciting. 100 percent would like to play it again. 60 percent of them enjoyed using the physical objects and wearable devices, because they felt curiosity and interest in the activities. 20 percent expressed more interest in the objects than the wearables, while the remaining 20 percent enjoyed using the wearables. In the case of Group C, only three of the five kids expressed interest in participating again.

We obtained the following results from non-verbal messages [19]. The first reaction of the children when using the system for the first time was as follows: 40 percent of the children felt afraid, 40 percent were nervous and 20 percent were happy. After having used the system, our results showed that all the kids were positively surprised by the activities.

## 5 Discussion and Future Work

In this study, we have started by analyzing the potential benefits of using IoT and wearable technologies in the area of task-based language learning for young children. Once having analyzed the main motivation for this teaching methodology and the difficulties in introducing it into the school, we have identified the areas where the use of IoT and wearable technologies may have an impact. We then developed and evaluated a system prototype. Based on the feedback obtained from the children and teachers, and the data collected during the trials comprising a comparative analysis with traditional task-based activities, we have identified the following major areas that can benefit from the use of IoT and wearable technologies:

*Classroom management and organization*. The act of clearly identifying each sector and defining the tasks to be performed therein clearly contributes to the successful execution of the class sessions. Students feel comfortable moving around the classroom while carrying out the task. The use of the wearable and IoT devices proved to be an attractive way of interacting with the system from any location within the classroom [1]. The Visualization Board also proved to be an excellent vehicle for keeping all the kids informed of the tasks being performed. They kept consulting the outcome of their actions by referring to it. As expected, tangible objects were always preferred over the tagged flashcards, confirming that kids prefer to work with real objects [9].

*Learning experience*. The system has proved to be very useful in coordinating the steps to follow and establishing a familiar scenario, such as the one reported in [7]. The teacher is then able to focus on stimulating them to participate. Students receive continuous and immediate feedback from the system and the teacher. The wide adoption of this technology in the education sector will very much depend on the ability of designing a friendly editing tool capable of meeting teacher expectations. The successful adoption of IoT and wearable devices in task-based language learning for young children will clearly require the collaboration of teachers and system designers.

*Evaluating the effectiveness of the learning-teaching process*. The analysis of the data captured through the wearable and IoT represents an invaluable source of information. Based on the information obtained, the teaching staff can evaluate the level of engagement and progress of each student, as well as the effectiveness of the teaching approach. Similar to the findings reported in [8], we have found that the data captured by the wearable and IoT devices become an invaluable source of information to the instructors. Based on the analysis of the data captured, the instructors may plan other activities to address special needs, such as reinforcing the participation of some of the class members, or reviewing specific vocabulary or grammar principles.

*System usability evaluation*. At the end the sessions of groups A and B, the teachers filled a System Usability Scale (SUS) questionnaire [20]. The SUS questionnaire consists of a simple ten - item scale subjective usability assessment. The scale yields a single composite number representing a measure of the usability of the system. Our proposal scored 81.25 (out of 100), i.e., the teachers had a very positive view of the system.

*Class size*. Large class sizes have been one of the major issues preventing the wide implementation of task-based learning. From our trials and based on the feedback from the participating instructors, we have found that the use of IoT/wearable technologies frees the instructor from the burden of recording, and to a certain extent, from having to coordinate every move. This can be seen as a major benefit from the point of view of class session logistics by allowing the instructor to focus on students' performance. Studies have shown that young children level smaller classes led to students receiving more individual attention from teachers, and having more active interactions with them [21]. However, the recommended class size will very much depend on the actual scenario and activities to be performed.

From the evaluation of our system prototype, we have gained an insight into end-user expectations. One of the main issues to be addressed relates to the interactions that take place in a task-based learning session, and therefore the type of features required of the wearables and IoT devices. Some of the immediate issues requiring study are:

*Wearable features*. Since one of the main goals is to promote the use of the foreign language, it is clear from the analysis of the video material that the proposed solution will greatly benefit from the integration of microphones. As for the use of more sophisticated interfaces, such as Google Glass, such devices when used in the classroom could distract students, which is a particularly relevant issue when dealing with young children.

*System features*. Our trials have shown that record keeping is an area where the use of IoT/wearables will have a major impact [8]. However, the system should incorporate, among others, friendly access interfaces to the data obtained through the interaction between the IoT and wearable devices, and report preparation.

*Task preparation and costs*. The development of friendly interfaces and tools facilitating the preparation of task-based class sessions would contribute to the widespread adoption of a task-based language learning approach among the teaching community. The possibility of deploying a wide spectrum of scenarios would prove invaluable to the learning experience, including outdoor activities, as in [5]. Based on our experience on setting our system protoype, we can anticipate that once having defined the task, the teaching staff should be able to set the IoT and wearable devices within minutes. As for the cost of the proposed solution, the proposed solution can be developed taking into account that students may bring their own devices: a trend that it is gaining popularity due to the widespread use of mobile devices [22]. Such solution will further enable the integration of a wide spectrum of wearable devices.

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## 2.2 WIoTED: An IoT-Based Portable Platform to Support the Learning Process Using Wearable Devices

**Publication Data**

**ABSTRACT:**
In recent years, we have witnessed an exponential growth in the use wearable and Internet of Things devices to provide friendly and tangible interfaces for ubiquitous services. The digital transformation of private and public organizations has been largely spurred by the widespread use of mobile devices, such as smartphones, tablets and virtual reality gadgets. Tangible interfaces have further enhanced the quality of experience by enabling the customization of human–machine interfaces. This paper presents WIoTED: a platform integrating wearable and IoT technologies specifically designed for the delivery and support of learning/teaching activities. Among its main features, WIoTED introduces MovED: a wearable device designed to facilitate both the orchestration of enriching teaching environments and use by young learners. Based on numerous trials conducted under various scenarios, we have validated the operation of WIoTED in terms of the education delivery effectiveness: usability and user satisfaction. Our study includes a comparison in terms of the workload generated and response time bounds delivered by MovED with respect to a setup preferring the use of smartphones.

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# WIoTED: An IoT-Based Portable Platform to Support the Learning Process Using Wearable Devices

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**Abstract:** In recent years, we have witnessed an exponential growth in the use wearable and Internet of Things devices to provide friendly and tangible interfaces for ubiquitous services. The digital transformation of private and public organizations has been largely spurred by the widespread use of mobile devices, such as smartphones, tablets and virtual reality gadgets. Tangible interfaces have further enhanced the quality of experience by enabling the customization of human–machine interfaces. This paper presents WIoTED: a platform integrating wearable and IoT technologies specifically designed for the delivery and support of learning/teaching activities. Among its main features, WIoTED introduces MovED: a wearable device designed to facilitate both the orchestration of enriching teaching environments and use by young learners. Based on numerous trials conducted under various scenarios, we have validated the operation of WIoTED in terms of the education delivery effectiveness: usability and user satisfaction. Our study includes a comparison in terms of the workload generated and response time bounds delivered by MovED with respect to a setup preferring the use of smartphones.

**Keywords:** internet of things; wearables; system on chip; tangible interfaces; NFC; digital gap

## 1. Introduction

With technologies like interactive robotics [1–7], augmented reality, tangible user-interfaces, and smart mobile devices the educational landscape is rapidly transforming giving rise to new learning and teaching tools empowering students with a variety of devices and applications [8,9]. The most popular technologies are still traditional video consoles and desktop/laptop computers [10,11]. The advantages offered by these platforms in the classroom are numerous. They enhance positive attitudes in users while being appealing and encouraging and providing information at the click of a button. However, their use requires that students stay in a single location looking at their computer monitors: a factor which inhibits peer-to-peer interaction and collaboration in the classroom. Smartphone popularity, particularly tablets and smartphones, has increased over the last years as an alternative or complementary solution to support learning and teaching classroom activities. These devices present many advantages, namely usability, portability, versatility, adaptability and an ability to customize individual experiences.

In the context of the teaching and learning processes, smartphones allow overcoming the temporal and physical boundaries of the classroom, since information is omnipresent and no longer limited to a specific time and place for learning [8]. Many recent studies explore the benefits, adequacy or potential risks of making use of smartphones as a vehicle for the education delivery process to young learners.

In fact, numerous studies found that smartphones can have a negative impact on learning through distraction or isolation [12].

Among the latest information and communications technologies, wearable and internet of things (IoT) technologies may be an alternative to the use of mobile devices. Ubiquitous computing, pervasive computing, internet protocol, sensing technologies, communication technologies, and embedded devices can be merged in order to set-up scenarios where the real and digital worlds meet and symbiotically interact [13]. That is to say, wearable and IoT technologies have the potential to completely transform the classroom where the smart object becomes the building block of the wearable and IoT vision [14,15]. We argue here that such platform will be of particular interest on the education delivery process to young learners. It is at this early stage of education that students learn based on experience and continuous interaction with their environment including their peers. The use of wearable and smart objects should serve multiple purposes. First, they should facilitate communication between end users, students and teaching staff, and the education delivery and feedback offered by the platform. Furthermore, the platform will also enable the automatic recording and visualization of relevant clerical and control data, i.e., attendance control, achievements, difficulties and the level of participation of each student [16,17]. All these latter data will enable the production of a fully-documented progress report.

However, the use of wearable and IoT technologies still has to make its way in education delivery to young learners [18]. Most current wearable-based education delivery platforms are targeted to specific subjects, e.g., physical education [19], computer education [20]. Furthermore, most studies mainly focus on the use of a wearable device as opposed to consider the overall education delivery platform. To date, no studies have been carried out on the design, evaluation and adequacy of a wearable IoT education delivery platform designed for the classroom. Furthermore, most works do not report on the enhancements and further evaluation of a wearable having been tested in field trials. Towards this end, we argue that the design of an education delivery platform has to follow a holistic approach, i.e., bearing in mind the target teaching setting, end-user profile and wide variety of educational content material. In our case, our ultimate goal is to report on the design of a portable platform based on wearable and intuitive tangible human interfaces for bridging the gap between human and IoT to be used in different application areas. Our main goal herein is to address one of the fundamental question in the design and development of consumer electronics devices for the primary education classroom: can a structured IoT and wearable platform, such as WIoTED, leverage the learning and teaching processes to a new quality of experience?

The paper is organized as follows: Section 2 reviews the literature on wearables and IoT in education. Section 3 provides the rationale and technical requirements of our proposal. Section 4 describes the system architecture and software component of our proposal. Section 5 describes the design principle, operation mode and features of the education-delivery wearable device. Section 6 present the results of the validation tests and performance of our solution. Section 7 concludes the paper and outlines our future research plans.

## 2. Related Work and Background

Over the last decade, numerous research and development projects have explored the use of wearable and IoT technologies in education. In [21], Sandall reviews the literature aiming to identify how wearable technology can be used by teachers to improve instruction and how students may interact with the school environment. His study also reveals the lessons learnt and guidelines for the successful implementation of wearables in the classroom. However, he stresses the importance of involving the school authorities and teaching staff as a must for the successful implementation of wearables in the classroom. In [22], Joyce et al. report on an IoT-based ecosystem deployed in eight schools across England. The trials reveal the great benefits of sharing data being generated stimulating discussion and increasing student engagement in the learning process: a must in the case of a wearable IoT solution to be used by young learners.

To increase the motivation in physical education class, authors propose in [19] a system based on wearables (activity band) and a smartphone, combining the physical exercise with the game and simultaneously checking the movements and activity of the student. The activities followed the pedagogical goals of the South Korean primary education curriculum. The study revealed the great potential of combining sensor-driven physical exercise with brains-on content while keeping the players engaged through gamification. They highlight the need to involve the teaching staff in the development of activities aligned to the curriculum objectives. In [20], the authors show a construction kit that allows children and young people to both interact with wearables and understand their technological background. Through the use of sensors and actuators embedded in textile, the students are introduced the basics of IoT and wearable technologies, including system integration and programming principles. In [23], Sula et al. introduce an IoT platform to support the learning process and assessment of young learners' abilities in math. All these works offer multiple advantages, the information is dynamic and instantaneous, wearable devices allow mobility and continuous information.

In one of our previous works [14], we applied IoT and wearables technologies into task-based language learning for young children. The main objective was to study the use of wearables and IoT in an educational context. We use smart objects and wearables devices, based on smartphones worn on the body, enabling the creation of realistic scenarios. The students had to look for educational smart objects distributed in the classroom. They had to bring the educational smart object closer to the wearable, which each student wears. The instructions, task outcomes and feedback are shown on a screen. The system operation was validated and compared to the case when the same task was performed without using the wearable IoT facilities. The results were very positive, and the use of wearables and smart objects prove to be an excellent tool. Its use did not only relieve teachers of manually recording the tasks performed by each student, but it helped them to perform the lesson as planned.

We also observed the advantages of using the smartphones to interact with the environment, the student showed a higher level of participation and motivation with respect to conducting the same activity without the use of smartphones and smart objects. The use of the smartphone was limited to read the tag of the smart object and provide proper feedback: right/wrong object and accumulated responses. However, we avoided displaying on the smartphone further information, such as number of operations being performed, number of objects being properly identified, time elapsed, etc. Instead, all other information was displayed on a large projection screen. This was done to bring the attention of the whole group to a central point. In this way, the teacher can visually keep track of the group and properly conduct the class based on the student attitude towards the activities being performed.

From the results of our previous study, we realized that students should be given a simpler device than a smartphone to communicate with the system. A simple device should be designed taking the needs and profiles of the end-users: teachers and students. On the one hand, students should become familiar with the device in a matter of minutes and almost unaware of its existence by focusing mainly on the learning activity. Due to the many functionalities of smartphones, students often get distracted while focusing on the smartphone features. On the other hand, teachers should not be overloaded with maintenance tasks, such as the need for frequently charging the batteries or repairing screens. Furthermore, the use of smartphones at large poses other challenges: (1) the availability and number of required devices to provide a service to classes of up to 25 students, the Spanish classroom ratio in primary classroom; and (2) the high cost of smartphones.

In this paper, we provide a solution to these challenges by paying special attention to the design of a low-cost friendly wearable device particularly suitable for young children.

### 3. Study Case Requirements

The main objective of WIoTED is to develop a low-cost IoT wearable delivery platform comprising a user-friendly wearable device and system management interface.

### 3.1. User Requirements

In this study case we distinguish two main end-user profiles: teachers and students. Teachers should be offered a user-interface allowing them to operate and manage the classroom. The system interface must offer them the control and management of all the functionalities necessary to carry out their educational tasks: activities control, monitor and evaluation tasks. Students should be provided with devices preferably specifically designed for the target learning activities and education delivery mode. The system must be dimensioned to support at least 25 users: reliability and latency are the two key system performance metrics. It must be adapted to young learners, and provide different types of feedback such as auditory, visual, and sensorial. They are essential to gain the student's attention during the activity [24]. The wearable device must allow hands-free activity and mobility around the classroom. In this way, physical activity can be encouraged, which is a key factor in development [25].

During the design and development phase of our platform, the expert pedagogues also recommended that the education delivery vehicle should include a big screen equipped with speakers. This offers several benefits in terms of workspace awareness and a friendly management of the coordination of the activity [26]. The information and instructions should promote student participation and collaboration. All these requirements should contribute to avoid distraction from the main objective, i.e., the creation of an enriching and engaging educational environment.

### 3.2. Classroom Requirements: Management and Organization

Numerous studies have concluded that the classroom environment is influenced by the guidelines established for its operation, its users and physical elements [27,28]. When dealing with young learners, the classroom organization should be carried out taking into account the nature of the foreseen interactions between students [27]. Activities can be undertaken individually, in pairs or in groups. In a given scenario, an object may be associated with a real-world environment allowing children to perform tasks related to it. On the other hand, task-based lesson planning requires not only the preparation of materials and classroom organization, but also the establishment of reasonable expectations for student behavior. Monitoring the classroom and adjusting lessons accordingly are two important elements in the successful implementation of a task-based learning approach [28]. Providing timely feedback on the goals will help achieve the teaching goals. Students can see their progress on educational activity, how much they have completed, and how far they have to go. They also have to see the progress of their classmates.

In recent years, new educational approaches have been investigated to improve school academic performance and student's engagement such as participatory, active and collaborative learning [29,30]. Specifically, collaborative learning in the classroom have been identified by many as a key 21st century skill [31]. The main purpose of these educational approaches is to promote interactivity, face-to-face communication and collaboration in the classroom.

In the same way the movement integration is an interdisciplinary method of teaching that may lead to greater student learning outcomes and long-term knowledge acquisition [32].

Since WIoTED has been developed following the aforementioned educational approaches, the classroom should be organized into team areas, see Figure 1: each team represented by a color. Figure 2 shows the organization in one of our system trials in a Bulgarian primary school. The areas can represent different scenes corresponding to a given scenario. A main area can be set at the center of the room where the different groups can collaborate, and perform a common goal task for exchanging or bringing in smart objects associated with the class activity.

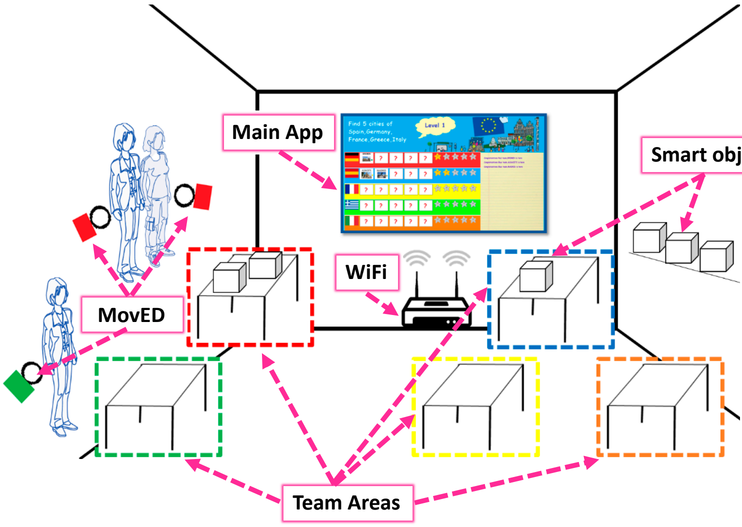


**Figure 1.** Classroom organization.


**Figure 2.** Bulgarian classroom setting.

## 4. WIoTED System Architecture

Based on the aforementioned system requirements, we describe the general architecture, individual components and operation of our experimental platform.

Figure 3 shows the system architecture of our proposal. As seen from the figure, our design has been centered on the end-users: teaching staff and students. We have therefore paid particular attention on the design of the end-user interface. This has involved the design of the custom-made wearable device, denoted as MovED in the figure.

The architecture of our proposal consists of two main core elements: a cloud-based activity controller and wireless network facilities. They provide the underlying control and data processing, data visualization and data communications services. A configurable collection of smart objects and three different types of device complement the system architecture: the visualization board, the teacher devices and the wearables, referred to as MovED in the figure. Throughout our work, we have paid attention on the design of the end-user interfaces and configuration of these last three devices. In the following, we describe the main features of all the components of WIoTED.

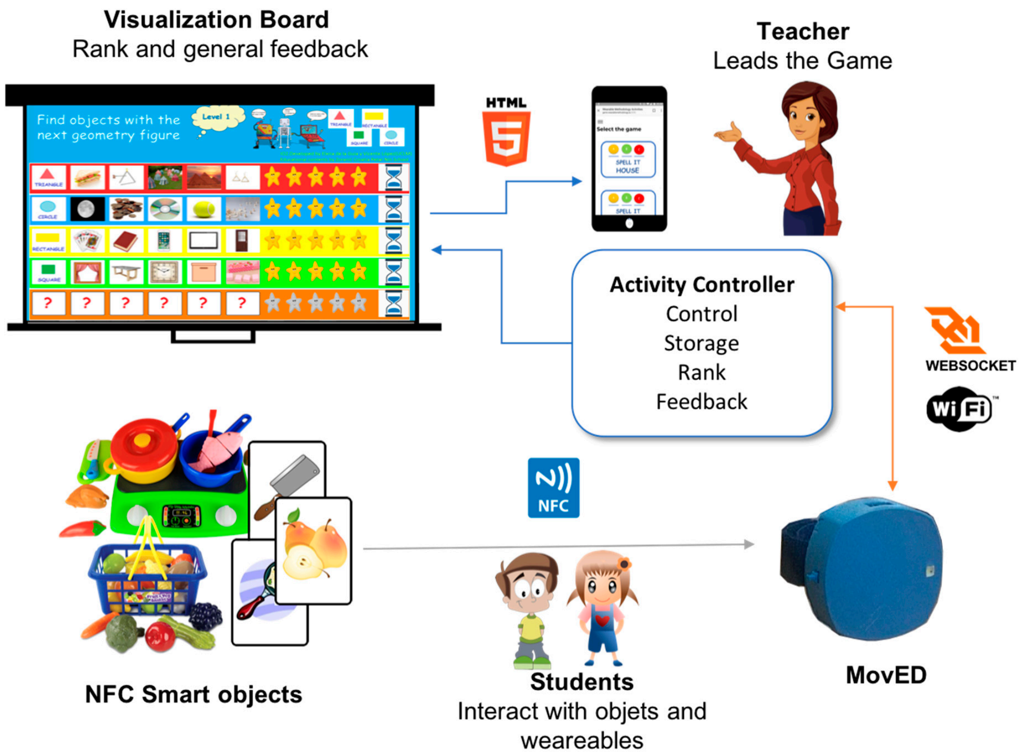


**Figure 3.** WIoTED system architecture for educational environment.

### 4.1. *Cloud and Network Facilities*

The Activity Controller consists of a cloud host, see Figure 4, whose main responsibility is to coordinate the time and sequence of the data and control messages exchanged by the various devices: wearables, desktop, mobile devices and visualization board. Its main components are a control system framework, a storage server and a Web server. We developed the control framework using JavaScript in the Node.js [33] environment. The Web server was developed using an HTTP server, Node.js and HTML5. The use of HTML5 should ensure the support of a wide variety of platforms: a must for a system to be deployed worldwide.

As shown in Figure 4, the control framework is responsible for coordinating the interaction among the three main end-user devices (interfaces): the wall screen (Main App), the teacher device (Teacher App) and the wearables. It also coordinates the access to the data server.

The Main App manages the Visualization Board. The display shows the educational activities, and the steps required to complete a collaborative task. It also shows user messages accompanied by positive feedback sounds. It has been developed in HTML5.

Regarding the Teacher App, this allows the teacher to manage the educational activity. The teacher can select an activity, and send motivational and collaboration messages to be displayed on the wall screen. It has been developed in HTML5.

As for the underlying network infrastructure, we have used WiFi technologies. Our choice was based on its popularity. All the system devices, including the MovED devices are equipped with WiFi radio interfaces. We use the WebSocket [34] protocol for interconnecting all the platform devices. This protocol implements a full-duplex communication channel per client via a TCP socket. In this way, we guarantee the reliability and time requirements of the application.

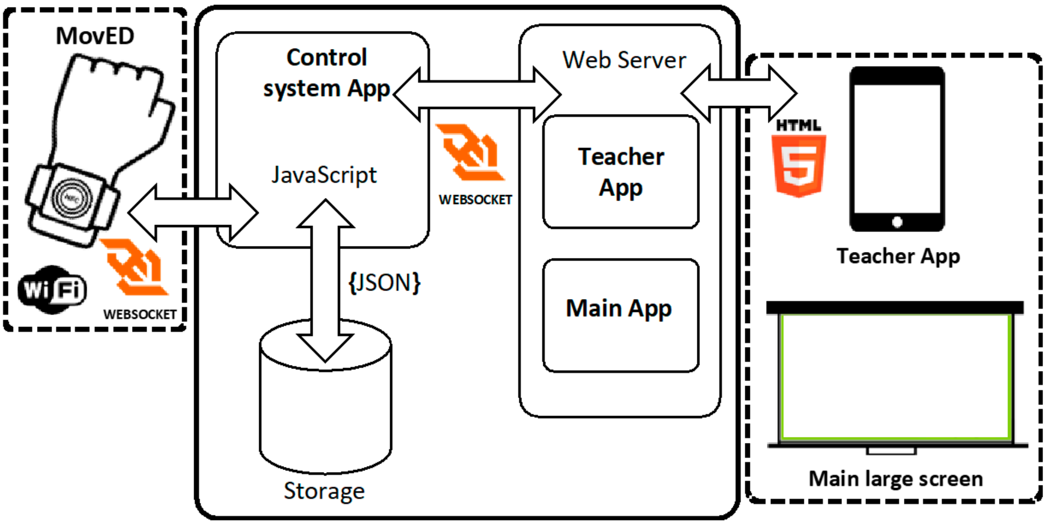


**Figure 4.** Activity Controller architecture.

*4.2. End-User Devices, Interfaces and Smart Objects*

The visualization screen consists of a large screen and speakers used to display the activity implemented by the main application. The main pieces of information displayed on this screen consist of: task outcomes, user feedback, and cumulative results per team, i.e., number of tasks performed. The size and location of the screen should be set in such a way that all students should be able to see the information being displayed.

Figure 5 shows the Main App interface. The interface is divided into colored rows each corresponding to the matching colored team of students: red, blue, yellow, green and orange. The activity instructions are displayed at the top of the interface. Each team can also check the progress of its activity represented by the images of the smart objects, properly matching the answer to a question.

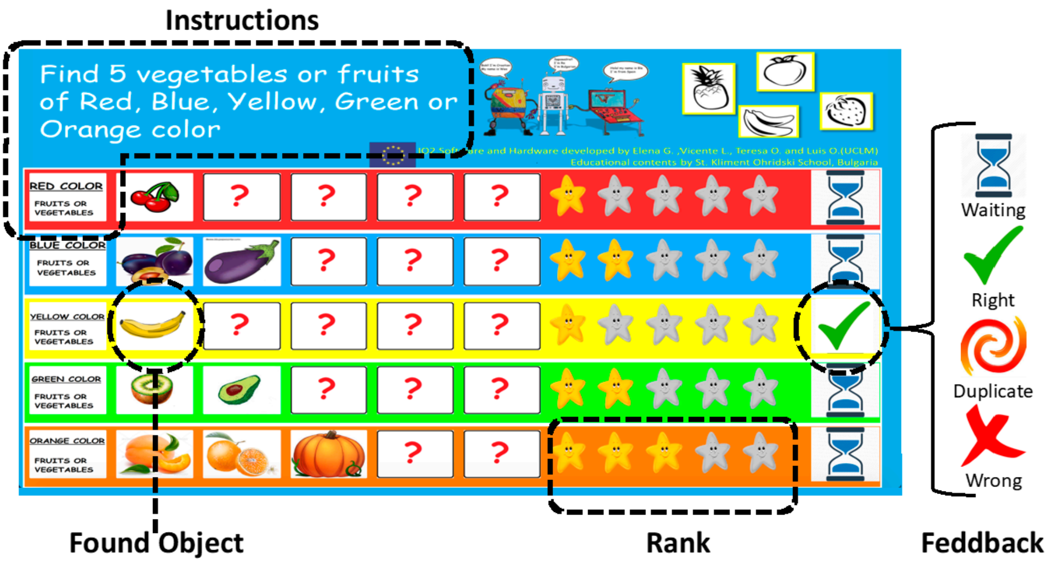


**Figure 5.** Main App interface.

Besides the progress of each team, the achievement rank of each team is also provided. Every time students interact using MovED, visual and sound feedback are provided. A representative icon of the right, duplicate or wrong interactions is shown accompanied by a pleasant sound in the case of a right answer or a strident one in the case of a wrong answer or duplicate one, respectively.

The teacher device may consist of a mobile device, laptop or desktop. The teacher makes use of the device to control and coordinate the educational activities of the classroom. Figure 6 shows the interface of the teacher application. The teacher can select an activity, send control, motivational and collaboration messages to the students.

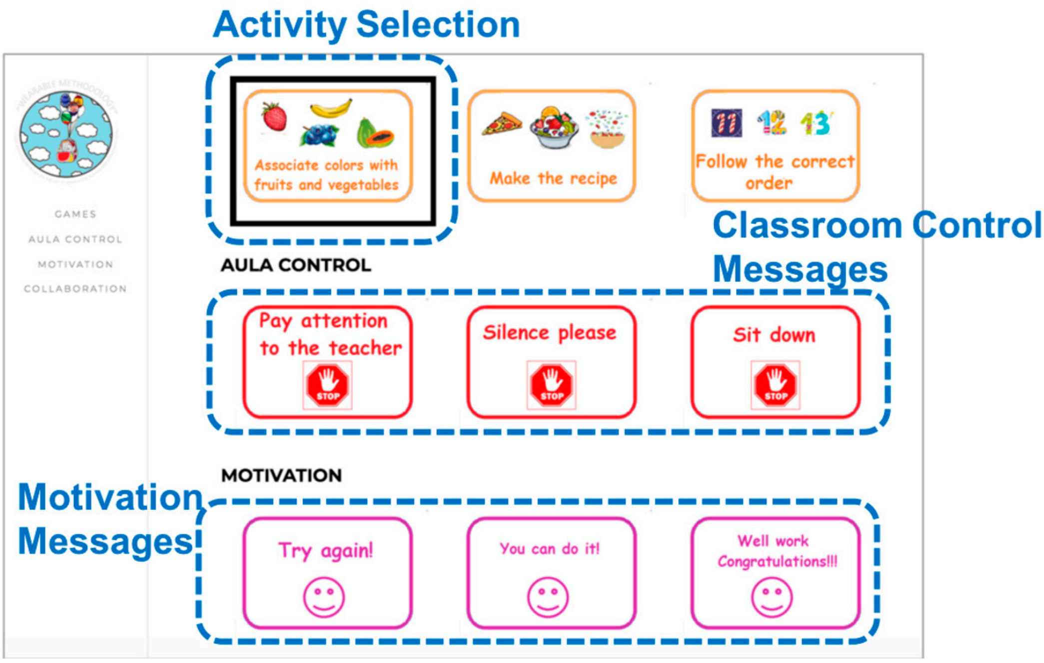


**Figure 6.** Teacher App interface.

In WIoTED, MovED is one of the central elements of our solution. It offers an intuitive user interface allowing mobility, portability and wearability around the classroom. MovED has been developed to support task-learning activities. In the next section, we will describe the design goals and main features of it.

The smart objects are educational contents related to educational task. The students should have access to them during the activity session. Each object should have been previously marked using an NFC tag. The number and types of smart objects used in a given class session should be determined on the basis of the learning activity, the level of complexity of the activity to be carried out and the main learning goals.

The data collected in each class enable teachers to derive deeper insights from their classroom. The teacher through a multi-platform application (smartphone, tablet, laptops, etc.) can interact with the system and the students.

Figure 7 shows the basic flow of information among the different components of the WIoTED. The Activity Controller is a cloud-based system application responsible of controlling the delivery of the teaching activities, recording the activities outcomes, issuing feedback and rankings messages. The visualization board displays the activities (teaching) material, instructions, and all feedback and ranking messages in response to the students' inputs. The teacher interacts with the system using a mobile device or desktop computer. During a class (activity) session, the teacher, via a friendly interface, has full control of the activity. The teacher interface application provides the means to launch, pause, refresh and terminate the teaching activities. The intercommunication between the teacher application and the system is performed via a WebSocket. For example, when the teacher selects an activity, the main app starts by displaying a message indicating the start of the activity. Once the activity starts, the students interact with the system by scanning the tagged (smart) objects using MovED. Each reading is sent via a WebSocket to the Control system app, which generates an update of the main interface, showing the success or failure, status of the activity, ranking, etc. It also sends a WebSocket with the feedback of success or failure to the corresponding MovED, which will vibrate and change color to green if successful or orange if unsuccessful or a smart object is scanned.

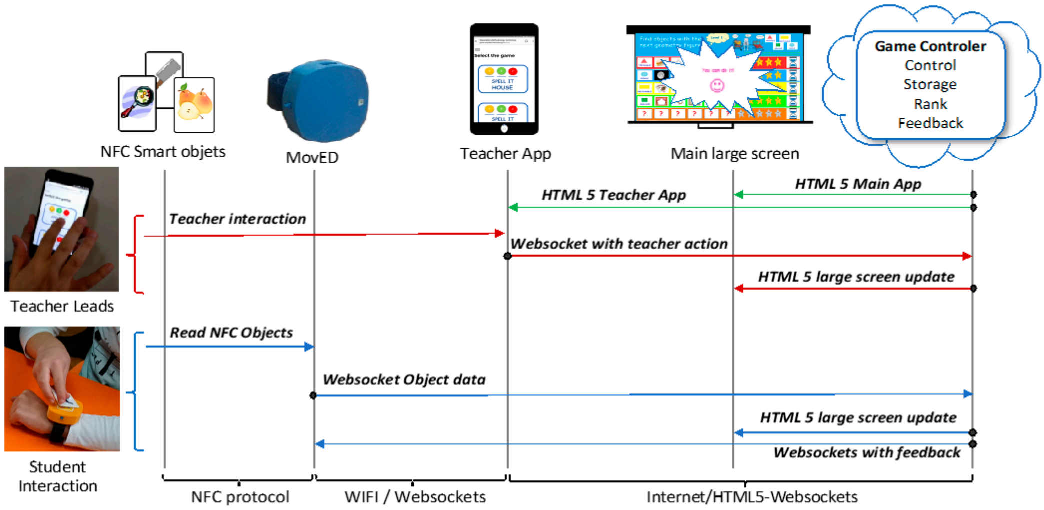


**Figure 7.** Flow of information that the different components of the WIoTED exchange.

**5. MovED: A Novel Wearable Internet of Things (IoT) Interface**

MovED can be seen simply as an NFC-based wearable IoT interface. To interact with WIoTED, the students must pick up a smart object and read its tag by simply approaching it to MovED. As already mentioned, MovED has been designed taking into account the application requirements and user profiles. The design has been conducted under the advice of professional experts in pedagogy. The main user requirements are: user friendliness and reliability. In order to meet the requirements, MovED has been developed using a low-power System on a Chip (SoC) high-end microcontroller and a low-power WiFi radio system. We have paid particular attention on the design of the physical layout including the placement of the feedback mechanisms, light-emitting diodes (LEDs), vibrator, and the power button and power charger input. Finally, the operation of MovED has been streamlined taking into account that the teaching staff has to keep track of the progress of each and every student.

*5.1. MovED Technical Specifications*

It is important to find the right balance between all system design requirements: low-power, reliability and low latency. We follow an iterative design methodology taken into account the feedback provided by professional pedagogy experts and end users. MovED comprises the following components, see Figure 8:

1. An SoC high-end microcontroller Wemos Mini D1 [35]. This SoC is suitable for create a wearable device for the compact sized, high speed and lightweight WiFi connection, and low power consumption. Table 1 shows the specifications of the SoC being used.
2. An NFC reader connected to the SoC through the I2C protocol, PN532 Elechouse nfc module v3 (Elechouse, Shenzhen, China) [36]. The PN532 is a highly integrated transmission module

for contactless communication at 13.56 MHZ that includes an 80C51 core-based microcontroller. The information exchange host system implements several interfaces. As already mentioned, we made use of the I2C interface due to its simplicity and straightforward integration into the overall SoC architecture.

3. Multisensorial sensory feedback actuators, red green and blue (RGB) LED WS2812 and vibrating motor Sourcingmap.
4. A 1000 mAh, 3.7 V lithium battery and a battery charger TP4056 (Nanjing Top Power ASIC Corp., Nanjing, China) [37]. In the stress evaluation tests of the second version of our device, MovEDv2, the battery lasted 3.5 h.
5. A haptic vibration motor. This actuator was added to the original design based on the feedback and recommendations of the teaching staff and users (students). A vibration produced in response to a right answer has proven very effective. Similar findings have been reported in the literature [38,39]. In addition, the color of the LED changes according to the operating conditions of MovED, ON/OFF, or following a tag read operation.

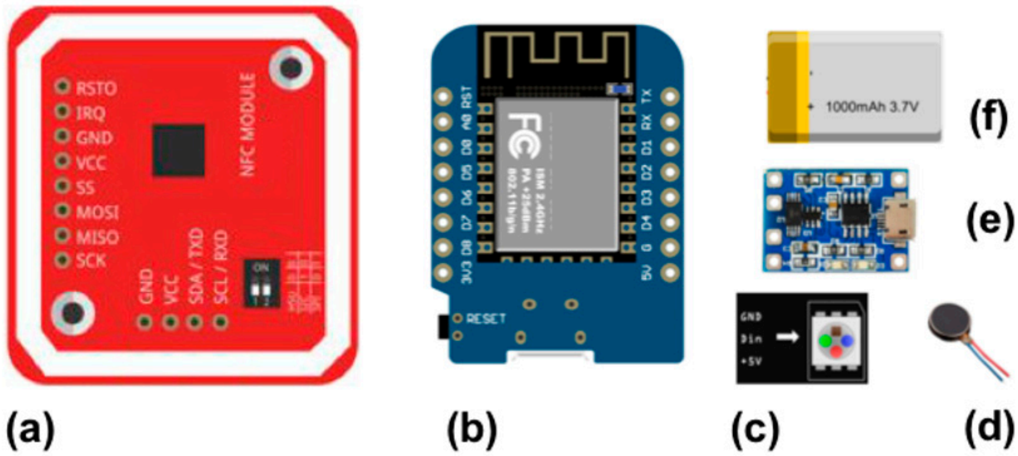


**Figure 8.** MovED Components. (**a**) NFC I2C module, (**b**) SoC, (**c**) Feedback red, green and blue (RGB) light-emitting diode (LED) (**d**) haptic vibration motor (**e**) battery charger (**f**) battery.

**Table 1.** SoC characteristics.

| Components | Description |
|---|---|
| Digital Ports | 11 I/O ports |
| Analog Ports | 1 input, 3.2 Vmax |
| Memory | 16 MB Flash, 50 kB RAM |
| CPU | 32 bits, 160 MHz |
| WiFi | 802.11 b/g/n |
| Power | 3.2 V–5 V |

Figure 9 shows circuit diagram of MovED. The SoC Wemos D1 mini is the main component together with the NFC PN532 module connected through the I2C interface. The sensory feedback is implemented by the WS2812 LED and the vibrating motor. The WS2812 is an intelligent control LED light source that includes the control circuit and the RGB 5050 chip in one package. The WS2812 is connected to the main SoC through a digital port using the NZR (non-return-to-zero) asynchronous data transfer communication scheme. The vibrating motor is connected to the SoC through a digital port using with a pulse width modulation technique (PWM). MovED is powered by a 1000 mAh, 3.7 V lithium battery that can be charged through the TP4056 module which is a complete linear current/constant charger for single-cell lithium ion batteries.

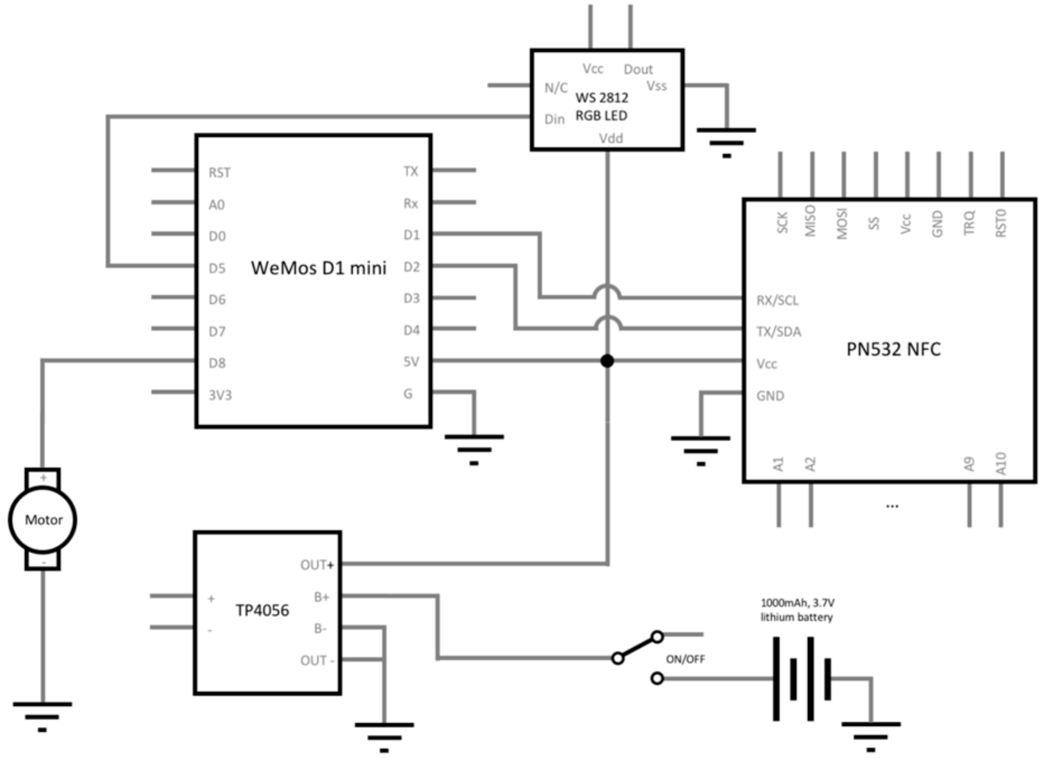


**Figure 9.** MovED electronic component connections.

MovED is powered by a 1000 mAh, 3.7 V lithium battery that can be charged through the TP4056 module implemented by a complete linear current/constant charger for a single-cell lithium ion battery.

As seen in Figure 10, the wearable is encapsulated in a prism-shaped plastic case. The case was prototyped and implemented using a 3D printer using five different colors: red, blue, yellow, green, orange. In this way, the professor and students can easily locate the team members; a feature particularly useful when the students have to collaborate. The edges of the prism have been rounded for safety reasons. The device includes a Velcro strap for a comfortable fit on the user´s wrist.

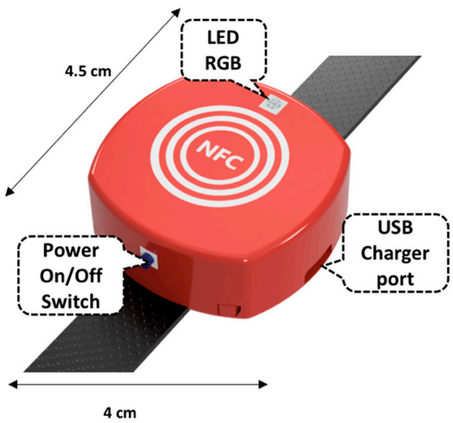


**Figure 10.** MovED physical design.

### *5.2. MovED Operation Specifications*

MovED operates under a client/server model, implemented in the C programming language. The interconnection control mechanisms were implemented in WebSocket while the JSON [34] format was used to encode the data.

As soon as the user turns on MovED device, it connects to the Activity Controller cloud of the WIoTED platform via the WiFi network. Figure 11 shows the operation flowchart of MovED. As long as the connection is on, the RGB LED remains blue and changes to white when successfully completed. Once connected, the device is ready to read and identify smart objects. When the students are required to perform an action, they can interact with the system by bringing the smart object closer to MovED. To avoid false readings, the MovED processes the smart object's readings to verify their validity before sending the reply to the Activity Controller. The valid readings are encoded in a JSON packet and sent to the Activity Controller through WebSocket protocol. The Activity Controller replies with the corresponding feedback, correct, wrong or duplicate answer. The LED changes to green and vibrates upon a correct answer. Otherwise, RGB LED changes to orange in the case of a wrong answer or duplicate answers. Figure 12 shows MovED user interaction.

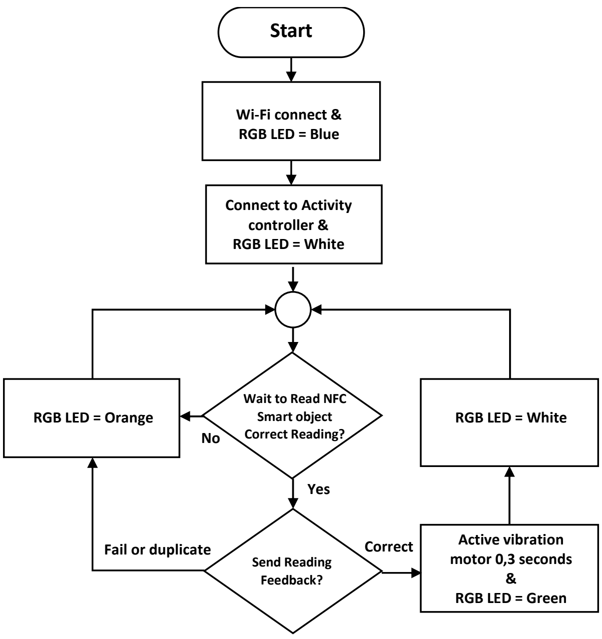


**Figure 11.** MovED operation flowchart.

**Figure 12.** MovED interaction.

A key factor in the usability of a system is the human–device interaction (HDI), simply defined as the interaction or mediation between human and devices. This concept involves the translation of human intention into devices' control commands, devices to devices communication and translating data into information comprehensible by humans. HDI is also called mobile human machine interaction [40], mobile human computer interaction [41], and human–mobile device interaction [10]. Below we explain in detail the concepts of human–device interaction in terms of time associated with the proposed platform.

Device–system interaction response time is defined as the time elapsed from the instant when the smart object is read and the instant when the wearable receives the reply from the activity control cloud. The operations performed during a DSI instance consists of the following: the device (1) detects the information of a smart object, (2) sends the data to the server. The server (3) processes the information and (4) replies to the device. The DSI response time depends heavily on the characteristics of the cloud, network and the wearable.

In order to estimate the lower bound, the shortest response time, let us assume the case when the user performs the right action, i.e., he picks and reads the right smart object. We can simply specify the device–system interaction response time, $T_{DSI}$, based on the system processing and communication times as follows:

$$T_{DSI} = T_{NFC} + T_{DATA} + T_{PROC} + T_{RPLY} + T_{FDBK} \tag{1}$$

where $T_{NFC}$ is the time required to read the tag, estimated in approximately 100 ms, $T_{DATA}$ is the data transmission time, it includes the process time required to encapsulate the data using the JSON; $T_{PROC}$ is the processing time required by cloud server to process the data and prepare the reply; $T_{RPLY}$ is the transmission time of the reply; and $T_{FDBK}$ is the time period to indicate the outcome of the user, i.e., the time length of the vibration fixed to 300 ms. Based on the system parameters, we estimated the overall $T_{DSI}$ to be approximately 600 ms. We will use this value on the evaluation reported in the following section.

From the point of view of the end-user, the reliability and the response time are the two main performance metrics of interest. In the following section, we will report the results obtained during our experimental system evaluation.

## 6. System Validation and Evaluation

In this section we present the results obtained during a series of tests allowing us to assess the performance of WIoTED and the wearability (usability) of MovED.

The main performance objective of the WIoTED is two-fold. We first evaluate the usability (wearability) of MovED. This is done in two phases. First, we evaluate two different versions of the MovED by varying the feedback mechanisms. We then conduct two trials. In the first one, the participants are asked to use MovED and then repeat the trial using a smartphone. The second objective focuses on the performance of WIoTED. In this case, we set up a worst-case scenario where we assume that 30 participants, 25 students and five teachers, make use of the system at the same time placing their requests at the highest possible rate.

All preliminary experiments were conducted in the premises of our research center, I3A Albacete. All participants gave their consent to carry out the experiment. During this phase, the participants were not required to register, i.e., no personal information was provided by the participants. Evaluations were made individually. Two evaluators explained the procedure. All the data generated during the test were automatically captured by the system and processed afterwards. The captured data did not store personal information of the students. All experimental sessions were conducted under the supervision of teaching staff in charge of the students. The trials were carried by observing the rules governing the funding agreements of national and regional agencies; and including the Regional School Board.

### *6.1. MovED Feedback Mechanism Validation*

Since one of our main objectives has been to develop a simple non-invasive wearable device, the number of feedback mechanisms were limited to a minimum. Accordingly, two different versions of MovED were implemented and evaluated throughout tests. In the first one, denoted MovEDv1, the LED and the vibrator were disabled. The second version, MovEDv2, incorporated the multi-color LED and the vibrator. Ten young students carried out an educational task using both versions of the MovED device. The task consisted of a spelling game. The students needed to look for 25 smart objects. The device was validated as fully operational; students were able to interact with the system properly and were able to solve the tasks. The device allowed mobility in the classroom.

In the case of MovEDv1, the user could not distinguish which state the device was in: on, off, reading, etc. For this reason, the user was even tempted to push several times the power button. As shown in Figure 13 (User Interactions MovEDv1), the number of duplicate interactions reported is very high. All participants performed at least two extra duplicates, User 2 and User 3. As for the worst cases, three out of the 10 participants performed twice the number of operations required. It is evident that the feedback provided by the device was not adequate; students were not sure if they had properly performed the action.

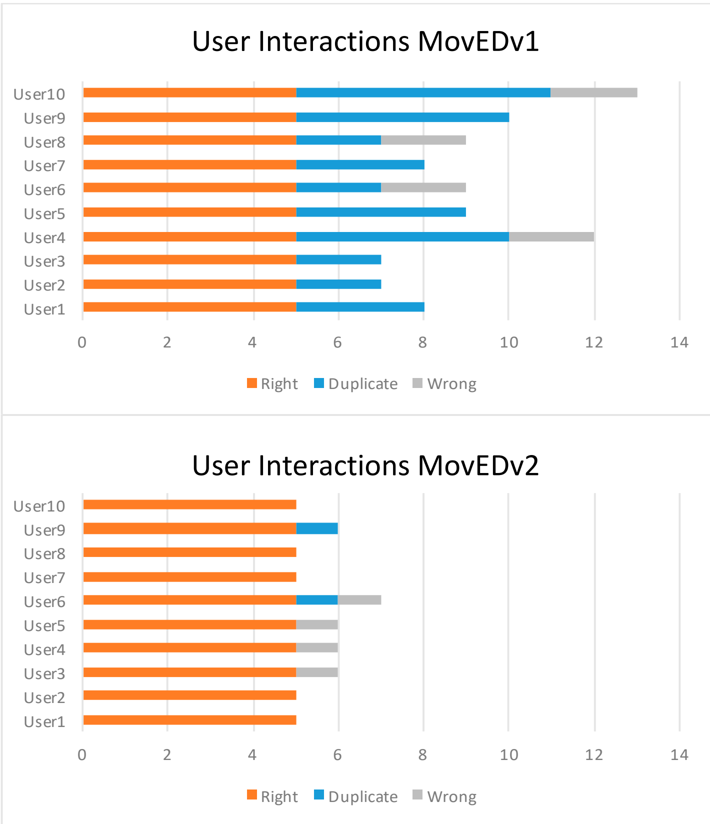


**Figure 13.** MovED interaction evaluation.

The same evaluation was carried out with MovED with two feedback components activated: and the RGB LED and vibrator. We repeated the same evaluation using a different set of words. Figure 12 (User Interactions MovEdv2) shows the results. Most students performed the task without having to repeat an action: only two out of the 10 repeated an action once.

### 6.2. MovED Usability and Interaction Validation

We have to bear in mind that the instructor will need to keep track of the tasks being performed by the students. It is therefore very important to ensure that all students get ready to operate their wearable with the minimum effort. The use of an application-specific device should minimize the possibility of errors. This is one of the main motivation of developing a wearable device specifically for its use in the classroom.

In the second part of this study, we carried a comparative evaluation on the use of MovED versus the use of a smartphone. In the case of MovED, the time required to get started, measured from the time it was turned-on until the application was available, was approximately 5 s. This time mostly depended on the time required to connect to the server. On the contrary, a smartphone requires more than 25 s to initialize. Once initialized, the user must select and launch the application. The total time required may then take more than 40 s; the total time may depend heavily on how familiar the user is with the device and application.

In this section, we analyze the MovED usability. We include a comparative test using MovED versus a smartphone. The main objectives of this evaluation were set to test the difference between the speed and the number of the interactions read by the MovED devices versus smartphone. The second metric, the number of interactions, does not only depend on the system processing capabilities characteristics, but more importantly on the user interface characteristics and user abilities. In other words, the aim of this test was to evaluate the usability of the two devices taking into account the user's (technical) background and preferences. Prior to the trial, we evaluated the DSI response time previously defined, see Section 5.2. From our tests, the average DSI response time was estimated at 600 ms. Therefore, the total interaction time was the sum of the user–system interaction time ($T_{USI}$) and device–system interaction time ($T_{DSI}$).

$$T_{CI} = T_{DSI} + T_{USI} \tag{2}$$

where $T_{DSI}$ is given by (1) and $T_{USI}$ is defined as follows:

In this second case, we limited the number of participants to five: two females and three males. All of them were familiar with the technology but none of them had previously used the NFC reader function in the smartphone nor the wearable. The devices consisted of MovED, a smartphone Quad-Core with NFC reader and a wireless access point connecting the devices to the Activity Controller.

The evaluation took place in consecutive order, see Figure 14. The procedure was as follows: each individual was informed about the procedure and goals of the test: to read the maximum number of smart objects tags during one minute. The smart objects were all placed on a table. Each individual made use of both devices one at a time. Once having completed the test, the participants were asked to fill a questionnaire indicating which one of the two device he/she preferred and why.

The number of interactions carried out in one minute was measured, see Figure 15. As seen in the figure, all the users were able to read a larger number of tags using MovED than the smartphone. This can be simply explained by the fact that the smartphone reader is more difficult to locate while MovED has been specifically designed for the target application. The participants their preference on using MovED as their first choice.

### 6.3. WIoTED System Validation

In this section, we report on the performance evaluation of WIoTED. Our objective was to evaluate the system response time as the number of active users increases.

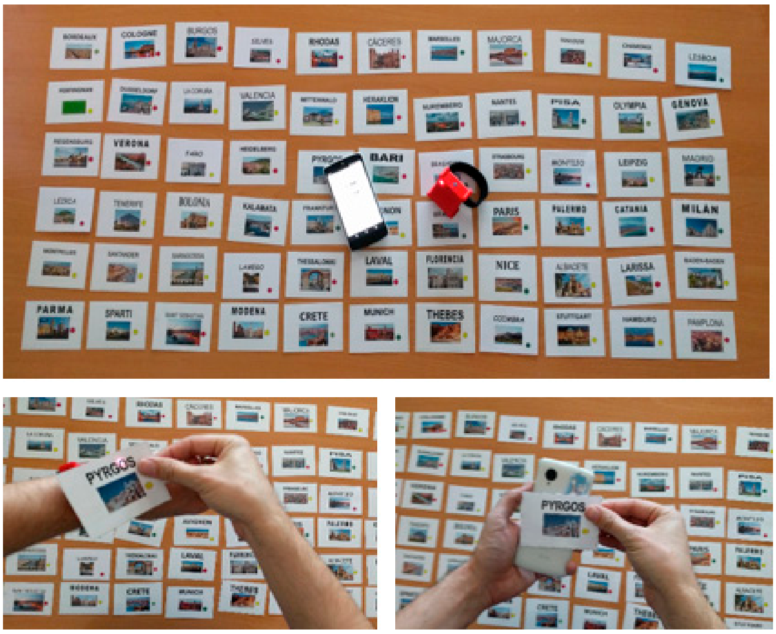

**Figure 14.** MovED usability evaluation.

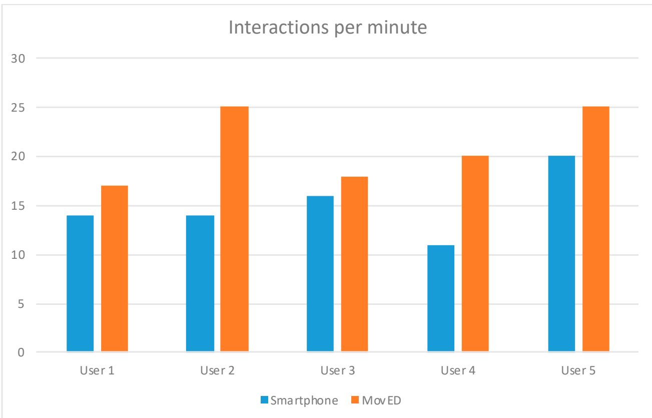


**Figure 15.** Interactions per minute.

Our evaluation setup consisted of a MovED and JMeter tool. The latter was used to emulate the traffic generated by a given number of MovED devices. The Activity Controller cloud server was implemented using a 2 Ghz computer with 2 GBytes of RAM and two Cores running Linux (kernel 4.4.0) and node.js 6.1. As a traffic generator, we used a PC running the Apache JMeter 4.0 [42] and generating WebSocket submissions. The WebSocket traffic generator PC and the evaluated MovED were connected to the internet via a dedicated IEEE 802.11 n WiFi access point.

The experiment consisted of setting a scenario where all users interact at the same time. The MovED device generated continuous smart object interactions (NFC tag reading operations) by fixing $T_{USI}$ to 0. As for the traffic generated by JMeter, the WebSocket messages issued a message waited for the reply form the server and upon the arrival of the reply waited another 600 ms before generating the following message. This process emulated the average time length, $T_{DSI}$, i.e., the shortest inter-arrival time between two tag reads in a class where the students are engaged on a task consisting on collecting various objects, see Section 5. The tests were performed by varying the number of active MovEDs: 1, 5, 10, 15, 20, 25, 30, 35, 40, 50 and 60. The measurements were made by the MovED device by determining the time that elapsed from the time when the WebSocket issues a message and the time when it receives the reply from the server.

Figure 16 shows the response times of all the experiments for the different system configurations. As seen from the figure, the average time for all the different system configurations is approximately 40 ms. In all different system configurations, we observe a number of longer response times. This behavior is due to the fact that the WiFi network was not exclusively used for our experimental trial. Furthermore, it is well known that a computer system may delay a reply. However, for all cases, the system was able to provide a good service: the response time does not exceed 100 ms; a boundary considered as acceptable for this type of interaction [43].

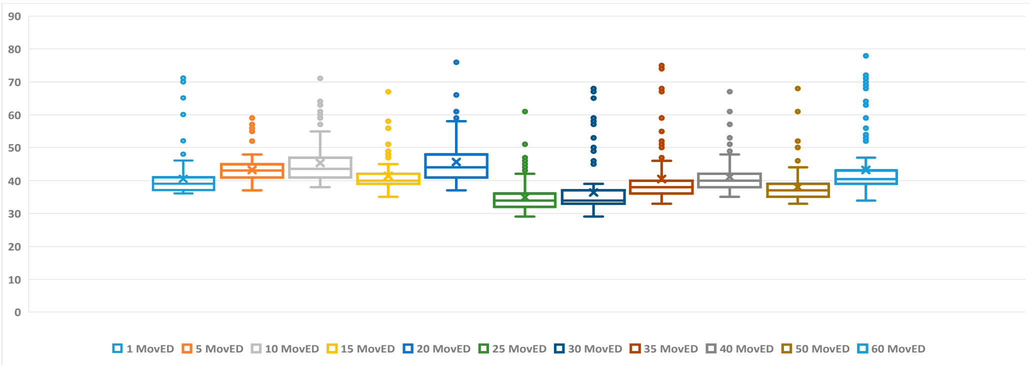


**Figure 16.** Activity Controller average response time.

From these results, we can conclude that WIoTED met the performance requirements, providing support to a group of 25 students and five teachers.

### 6.4. Implementation in Real Educational Context and Initial Validation

During the period between June 2018 and March 2019, more than 500 students and 20 teachers used the MovED in a series of English teaching activities based on learning games: spelling, vocabulary, verbs conjugation and grammar rules.

The student population consisted of 26 kindergarten, 150 primary school, 150 secondary school, 80 high school and 40 undergraduate students. The primary goal of these trials was focused on obtaining a first impression of the system and more specifically of the MovED as primary system interface. There was no pre-selection of students. No personal information was collected during the trials and the survey just simply consisted on the first impression of using a simple electronic device, MovED as the interface to WIoTED. Students performed the same set of activities using a smartphone and MovED. Due to the large number of students participating in some of the sessions, a group of up to five students had to share the use of a single MovED device.

The results were very positive: 100% of students wanted to repeat the activity. Up to 99.4% of the cases, students expressed their preference on using MovED over a smartphone due to their comfort, friendly and intuitive usage.

As a result of the positive welcome by the educational community, a European project has been conducted under the sponsorship of a European Erasmus educational project with the participation of four European primary schools [44]. The success of WIoTED has been mainly due to the intuitive and friendly interface, MovED. Students of all ages can almost instantly learn how to interact with the system. It is just matter of handling the tagged objects, scanning them and waiting for further instruction and feedback. As for the teaching staff, they have pointed out as the most valuable features: the availability of a device specifically designed for the classroom, integrating exclusively the elements allowing the students to actively participate in the learning process besides allowing them to keep track of the performance of each student during the class session. Furthermore, numerous members of the teaching staff have also pointed out the reliable operation and easy maintenance as relevant features.

## 7. Discussion

The latest developments in the area of open-source and inexpensive electronic devices and computational platforms have spurred the deployment of novel solutions in many of our daily activities, e.g., e-commerce, education and health service provisioning [45]. The work herein addresses the following challenge: can a platform, such as WIoTED, making use of wearable and IoT technologies enrich classroom learning/teaching activities?

The results and analysis of the lessons learnt from the development and experimental trails of WIoTED can be summarized under the following five areas:

- Application requirements: the fact of including as main design parameters the application requirements, i.e., educational services and the profile of the target end-users, teachers and students, has proven to be key for the acceptance of the application. Even though the system, and in particular MovED, has been designed for young learners, primary school, teenagers and even undergraduate students have welcome MovED as a natural and friendly interface device. Throughout the trials, the participants have focused on the activity with little or no attention paid to the device. The use of a more sophisticated device, e.g., a smartphone, has proven to be a major source of distraction.
- Design and development of the platform. As for the technological issues, our design has been based on off-the-shelf technologies such as WiFi, and NFC and open source hardware and software technologies JavaScript, HTML5, Node.js and WebSocket. As for the physical and sensorial components integrated into MovED, we have counted on feedback from the end-users. Our initial design has benefit from the comments and suggestions of the teaching staff. The addition of feedback mechanisms has resulted in an improved version of MovED, namely MovEDv2, see Section 6. Students felt more comfortable using MovEDv2 resulting in a significant reduction of the number of meaningless interaction attempts, see Figure 13. As a result, the power consumption was significantly reduced which clearly shows the benefits of counting with the end users' participation in the design and proof-of-concept processes.
- Operating performance. Following current trends, MovED was developed using open-source electronics devices [45]. We paid particular attention to using low-power devices due to the user requirement. Teachers should not be bothered by having to recharge batteries during a teaching journey. This feature is particularly relevant as the number of devices being deployed may increase as a function of the class size. In this sense, the deployment of a multiplug or even a wireless charger may prove beneficial in a real setup by allowing to easily charge multiple MovED devices.
- User acceptance. WIoTED and in particular MovED has been evaluated by students ranging from pre-school to university. All of them have welcome the use of MovED as natural and friendly system interface. As for the teaching staff, they have also found that MovED allows them to keep track of the students' involvement in class activities. The design of MovED has benefited from the input of the teaching staff. As further sensing actuators are becoming available, we expect to explore further improvement in this area. For instance, the inclusion of a gyroscope into the MovED device may prove useful to develop the kids locomotor skills. Some works have been recently reported in the development of wearable technology for the training of workers in the framework of Industry 4.0 projects [46].
- Potential use in other areas. Among other potential fields of application of WioTED, we aim to further explore the use of wearable and IoT technologies in the field of elder cognitive therapies. Some of our initial results have shown the great potential that this technology may have in assisting an increasing population of elder people [47].

## 8. Conclusions and Future Work

We present a platform based on wearable and intuitive tangible human interface for bridging the gap between humans and the IoT. The platform has been initially tested and evaluated with great success. Students of all ages and language backgrounds tested the system through different quizzes related to foreign languages, geography and math. WIoTED has been developed using off-the-shelf IoT technologies, such as NFC, SoC microcontroller, WiFi, WebSocket, JavaScript and Web apps on the cloud. This makes it easier for other devices or new developments to be easily incorporated into the system. One characteristic of a useful platform is its ability to support various and complementary applications.

As part of our future work plans, we will further explore the capabilities of the WIoTED system taking into account the user feedback. We will also improve the Activity Controller by adding machine-learning techniques to automatically analyze the data collected during the activities: a must to validate the full potential of WIoTED.

As for MovED, we will explore adding other sensors and actuators to enrich its capabilities and fields of application. Some of the immediate fields of application include scenarios such as cognitive rehabilitation and the prevention of Alzheimer' disease and dementia.

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## 2.3 Data Capture and Multimodal Learning Analytics Focused on Engagement With a New Wearable IoT Approach

**Publication Data**

**ABSTRACT:**
Increasing school dropout rates are a problem in many educational systems, with student disengagement being one significant factor. Learning analytics is a new field with a key role in educational institutions in the coming years. It may help make strategic decisions to reduce student disengagement. The use of technology in educational environments has grown significantly and, with it, awareness of the importance of student engagement. We exploit tracking and wearable technologies to increase user engagement in learning processes, exploring also the area of multimodal learning analytics (MMLA). We use wearables and Internet of Things for education, an interactive and collaborative system designed to improve motivation and learning. This article presents the results obtained in different experiments conducted in a secondary school in a long-term participatory learning context. The captured data were analyzed and used to identify different students' behavior patterns, showing their progress and motivation. Subsequently, from the captured data and aiming at a decision-making phase, we used machine learning techniques and MMLA methodologies to construct models able to "explain" when student engagement is present, so this knowledge can later be exploited. In particular, we chose decision trees and rule systems based on a set of variables with proven relevance to the problem. The evaluation of this novel engagement classification system confirms the high performance of these variables. The rules obtained, which can be easily interpreted by a nonexpert, help the teacher to observe, analyze, and make decisions with the purpose of fostering engagement.

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# Data Capture and Multimodal Learning Analytics Focused on Engagement With a New Wearable IoT Approach

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***Abstract*—Increasing school dropout rates are a problem in many educational systems, with student disengagement being one significant factor. Learning analytics is a new field with a key role in educational institutions in the coming years. It may help make strategic decisions to reduce student disengagement. The use of technology in educational environments has grown significantly and, with it, awareness of the importance of student engagement. We exploit tracking and wearable technologies to increase user engagement in learning processes, exploring also the area of multimodal learning analytics (MMLA). We use wearables and Internet of Things for education, an interactive and collaborative system designed to improve motivation and learning. This article presents the results obtained in different experiments conducted in a secondary school in a long-term participatory learning context. The captured data were analyzed and used to identify different students' behavior patterns, showing their progress and motivation. Subsequently, from the captured data and aiming at a decision-making phase, we used machine learning techniques and MMLA methodologies to construct models able to "explain" when student engagement is present, so this knowledge can later be exploited. In particular, we chose decision trees and rule systems based on a set of variables with proven relevance to the problem. The evaluation of this novel engagement classification system confirms the high performance of these variables. The rules obtained, which can be easily interpreted by a nonexpert, help the teacher to observe, analyze, and make decisions with the purpose of fostering engagement.**

***Index Terms*—Engagement, Internet of Things (IoTs), learning analytics (LAs), wearables.**

## I. Introduction

SCHOOL dropout is a serious problem for students, society, and policy makers [1]. According to expert estimates, in 2017, an average of 10.6% of young people (aged 18–24) in Europe were early leavers from education and training. More precisely, in Spain, an average of 18.6% of young people are school dropouts [2]. One of the main predictors of school dropout is the feeling of disengagement or lack of motivation [3].

Disengagement is the action or process of withdrawing from involvement in an activity, situation, or group. For this reason, identifying early indicators of disengagement may help schools to remedy the problem before it can escalate to absenteeism. Disengagement could be described as follows. According the emotional dimension, the students have negative reaction, frustration, and boredom. The cognitive dimension reflects the students need to understand complex ideas and it is a challenge for them. The behavioral dimension is related to disrupt behavior, or not following classroom rules and the social dimension withdrawing from collaboration or social interaction with peers [4]. Students can be disengaged even when physically present in the classroom. In fact, many students who attend class remained disengaged. The proposed system has two main objectives. The first is to detect in real time the disengaged students, and the second is to motivate them through new technologies and devices, based on interactive learning activities in which the student can participate through wearables devices and smart objects.

Taking into account the importance of detect student disengagement and the same time increasing student engagement to improve the relationship with academic achievement, learning analytics (LAs) has become a key factor in the learning process.

There are multiple definitions of LA. We can say that LA is the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs [5]. Fig. 1 shows the LA cycle [6]. It offers teachers and education designers a new, practical source of information to complement their own observations and evaluations: a gold mine of data about student behavior and learning needs [7]. LA is, then, the process of using data to improve learning and teaching. We can find some applications in online platforms, such as Moodle (a number of systems integrate with Moodle to provide LA information [8]). It is clear that LA can also provide useful insights into student engagement.

The use of novel wearable technology also offers new opportunities to refresh classic areas of the curriculum and to increase student engagement [9].

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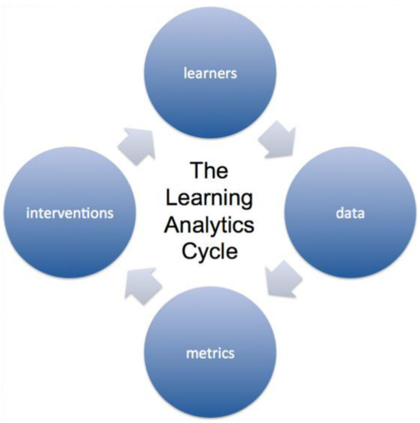


Fig. 1. LAs cycle [6].

The enormous amount of data collected with these technologies encourages us to use machine learning (ML) techniques to classify them. We delve into the world of MMLA, a research field located at the crossroads between learning science and ML.

We are interested in studies focused on data analysis about engagement in a real classroom (students and teacher learning face-to-face in the same space) using wearable technology. In this article, we propose the wearables and Internet of Things (IoTs) for education (WIoTED) system based on IoTs technologies and wearable devices monitoring data in real time. The system saves information about the type of student interaction, time, progress, etc., while he/she is doing the learning activities in class.

We used this system over a school year, analyzed the data obtained, and categorized the students' behavior. The methods applied were the next: exploratory data analysis (EDA) [40] to summarize their main characteristics, and then ML methods to identify the students' engagement or disengagement in the learning activities. In this way, we automatically provided the teacher with information about their students' engagement, explained with variables such as students' attention, curiosity, control, and relevance.

Thanks to these systems and methods, a proposal indicating the student engagement or disengagement level in class was made. In addition, we analyzed and classified the information stored, using ML techniques, so that, ultimately, the teacher can make decisions in real time, learn more about the students, their behavior, learning, etc., consequently, being able to take measures to improve learning, engagement, educational quality, etc.

The results obtained by this type of analysis can be considered valuable information for any teacher since it will allow them to know how each student is evolving, their behavior, and learning progress. Most importantly, they will be able to detect student disengagement and look for solutions and make decisions. If this diagnosis is made on time, which is possible with the solution proposed in this article, they may be able to reformulate the teaching strategy with the aim of fostering these specific students' involvement. Therefore, monitoring students in the classroom could help teachers provide better support, try different techniques to increase motivation, enhance tutoring, and adapt content or activities.

Our intention is to achieve the following objectives with the use of the WIoTED system and wearables.

1) To create new classifications of student interaction and obtain patterns of behavior to know and understand student progress and motivation in real time.
2) To create a novel classification of engagement in a classroom, carried out concurrently, in the same space (collocated-synchronous), and using face-to-face interaction.

Through different methods of ML, the data collected over a complete academic year at a secondary school were processed to construct models.

Considering the results obtained, we can also say that the current work has succeeded in answering the following research question: Can the WIoTED proposal provide information about student engagement using multimodal learning analytics (MMLAs) methods?

Our research was mainly inspired by the following works: [10]–[12]. In [10], LA is used as a positive contribution to the field of computational practices, such as programming. The authors develop a solution to categorize and understand students' clicks in Scratch. They detect patterns in students' behavior when developing solutions for assignments. Cocea and Weibelzahl [11] investigate whether log file data analysis can be used to estimate the motivational level of a learner. Logging the users' interactions in educational systems gives the possibility of tracking their actions at a highly detailed level. Data mining and ML techniques can give meaning to these data and provide valuable information to improve learning. The results suggest that time spent reading is an important factor for predicting motivation. In addition, performance in tests was found to be an important indicator of the motivational level. In [12], the authors present an approach on how the usage of virtual learning environments (VLEs) can be traced and used to enhance teaching quality so as to improve engagement. The aim is not to predict the performance of students from the collected data or to simply define a set of pre-established metrics from the digital data contained in the VLE, and monitor them, indirectly inducing an assessment regime. The authors measure the motivation of a student in a particular task, in a given subject, and on a specific day. They also show, with another case, how LSs contributes to the enhancement of learning and teaching processes by defining, measuring, modeling, and formalizing computationally the constructs associated with learning dispositions.

This article is organized as follows. Section II presents the background of the article. Section III describes the WIoTED system and the method used to collect the data. Section IV describes the material and methods applied in this article. Section V presents the results, where both quantitative analysis and visualizations are explained. In addition, it presents the new engagement classifications and behavior patterns obtained after processing the data with different techniques (EDA, ML, etc.). Section VI is dedicated to the discussion. Finally, Section VII presents the conclusion and directions for future work.

## II. Background

### A. Student Engagement

Engagement has consistently been found to be an effective predictor of learning performance in the long term. Due to its importance, multiple experiments have been conducted in order to obtain relevant variables that help us identify student engagement. According to Liu *et al.* [13], engagement can be measured by a flow scale based on four dimensions of flow perceptions: 1) interest; 2) curiosity; 3) control; and 4) attention. The concept of flow is related to intrinsic motivation, and recent experiments have shown that intrinsic motivation produces engagement in learning activities, better conceptual learning, and higher persistence in learning activities [14]. Malone [15] proposed a taxonomy of intrinsic motivation composed of four key motivation factors that, when activated, improve learning: 1) challenge; 2) curiosity; 3) control; and 4) fantasy. Previous works have used this theoretical basis to obtain information about motivation [16]. Keller [17] presents the attention, relevance, confidence (ARC) model based on the idea that resources, procedures, and activities enhance motivation to learn. The four categories described are the following: 1) attention; 2) relevance; 3) confidence; and 4) satisfaction. Taking into account the work described in [15]–[18], we chose the following variables to obtain information about student engagement in class: 1) attention; 2) curiosity or challenge; 3) control or confidence; and 4) relevance.

### B. Learning Analytics and Multimodal Learning Analytics

LAs permits the analysis of students' behavior patterns when they interact with educational and technological tools. In this way, we can analyze the learning environment and outcomes, and draw conclusions to enhance students' motivation and the learning process [19].

In [20], Viberg *et al.* analyzed 252 papers on LAs in higher education published between 2012 and 2018 to show whether LAs improves learning outcomes, supports learning and teaching, is deployed widely, and is used ethically. The results demonstrate that, overall, there is little evidence of improvements in students' learning outcomes (9%) or learning support and teaching (35%). Similarly, little evidence was found for the third (6%) and the fourth (18%) proposition. Therefore, it is necessary to continue working in this area and to carry out experiments that lead to clear and real conclusions about the benefits of LA and MMLA.

In [21], Nistor and Hernández-Garcíac present six examples of the application of different LA approaches using various data types, aiming to achieve different goals, and employing different instruments and methods: 1) eye tracking; 2) automated online dialog analysis; 3) survey data from school ecosystems; 4) log data analysis at individual; 5) collaborative level; and 6) visual LAs applied to IoTs data. The analysis of various data types provides improved insight into educational processes that can be continued and extended by predicting the subsequent evolution and by choosing interventions. Intensive and purposeful learning activity has many indicators that can occur simultaneously so that the detection of only some of them may predict final success with high accuracy.

Clickstream analytics is a technique used in web applications to determine how visitors behave on a website. Through the collection of clicks in the different parts of the web pages and an analytical and visualization tool, you can get an idea of the visitor's behavior [22], [23]. In [10], Filvà *et al.* used the clickstream technique to obtain valuable data analysis in order to understand how students proceed in learning and programming environments and thus improve their tutoring and support to students.

Many learning management systems (LMSs) have started to incorporate LA into their core. An example is Moodle, an open source LMS that implements transparent next-generation LAs, using ML backends that go beyond simple descriptive analytics to provide learners and teachers with predictions of learner success, and, ultimately, diagnosis and recommendations [24]. In [25], a new plugin for LA in Moodle was developed.

In [26], Zhang *et al.* used LA to explore some factors influencing students' engagement with teamwork and to reduce the "free rider" effect in group learning with the help of slack. They examined the role of slack in student engagement in collaborative learning. Specifically, they examined whether the openness and visibility of each group member's contribution on slack could promote student engagement. The data were analyzed using SmartPLS. The results showed that mutual trust, social influence, and reward valence among students can promote their teamwork engagement. Furthermore, teamwork engagement can promote students' learning and work satisfaction.

The use of online learning technologies allows institutions to gain new insights into student engagement and enables them to assess academic risk and predict success in learning. The book [16] outlines how LAs and other feedback can be used to gain insights into students' engagement and their learning experience. The authors argue that the power of LA is significant. If effectively used, it can improve institutional understanding of student learning, student behavior, and core areas of the curriculum and pedagogy that are key to students. Analytics such as learner interaction with peers and teachers and comments on discussion questions and blogs can be used to gain insights into the level of engagement. Effective use of learning technologies can elicit information about student behavior and engagement in learning.

If we go one step further and consider a set of multimodal sensory inputs, which can be used to predict, understand, and quantify student learning, we are working with MMLAs. MMLA is a research field located at the crossroads between learning science and ML. In [27], we can see definitions of MMLA and a review of MMLA distinguishing between past and present papers and future challenges. In [28], Blikstein studied patterns in how students of different ages and expertise levels complete tasks, such as programming, building a robot, designing a device, or conducting a scientific investigation. Thanks to multimodal interaction, new data collection and sensing technologies are making it possible to capture massive amounts of data (computer logs, activities, wearable cameras, wearable sensors, biosensors, gesture sensing, infrared, etc.). The author proposed a proof of concept of novel assessment techniques using several modalities. In [29], Di Mitri *et al.*

conducted a literature survey of experiments using multimodal data to frame the young research field of MMLAs. This survey led to the formulation of a new model, the MMLA model, whose main objectives were mapping the use of multimodal data to enhance the feedback in learning, showing how to combine ML with multimodal data, and aligning the terminology used in the field of ML and learning science. In addition, three main challenges were identified.

1) There is a lack of understanding of how multimodal data relates to learning and how these data can be used to support learners achieving the learning goals.
2) It is still unclear how to combine human and machine interpretations of multimodal data.
3) The fields of ML and learning science use different terminologies that are ambiguous and need to be aligned.

This article could be considered as a MMLA proposal/system because, through wearables, it saves data on every interaction carried out by the student in the learning environment.

### C. Machine Learning

ML is a field of computer science that studies how to make computers learn from experience. The final aim is the capability of making predictions or decisions given a new and unknown scenario. The learning process is based on the ability of an algorithm, typically built on a mathematical model, to extrapolate knowledge and decisions from a set of given samples. ML is currently being applied to a wide variety of problems in different areas, including life sciences, stock market analysis, videogames, marketing, or human computer interfaces.

For the scope of this article, we will mainly focus on a particular ML task, known as supervised learning or classification. Supervised learning constructs a hypothesis based on how the inputs of each sample relate to the corresponding expected output or label. Therefore, the aim of a supervised learning algorithm is to learn a function that effectively predicts the corresponding output for that sample. Problems where the output is numeric are called regression problems, whereas if the output is a class label (from a predefined set of possibilities), we have a classification problem. The learned models able to determine a class or label from a set of observed features are called classifiers.

A classifier is, therefore, a model that, given a certain configuration of the input parameters or features in the problem, is able to predict the corresponding class. When learning the model, the algorithm uses prelabeled cases so that it can learn from real cases and extrapolate how to classify future unknown configurations. In this article, we attempt to determine from the input whether there is engagement.

Extracting useful information represents a novel challenge involving ML, data mining, LAs, and MMLAs. Educational data mining is the science of extracting useful information from large data sets or databases containing students' interactions during their learning, for example, in a virtual environment. LA is composed of several steps, where the first is strictly related to educational data mining for capturing data by ML algorithms. In [30], Sciarrone discusses the intersections and correlations between these three areas of research, discussing their relationships and steps to give a useful overview on the learning processes from different perspectives. Different models are presented and discussed, highlighting their main characteristics and their relationships with educational data.

The collection of big data sets will ultimately lead to conclusive information about learning, and is a challenge that the field of LAs must address. The teacher is best placed to determine whether student patterns of behavior match the pedagogical reasons for that activity leading to student learning [31].

We have generated rule systems, obtained via decision tree models. Two main reasons supported our choice: they are relatively fast to be learned and even faster when classifying, and the resulting models (for manageable dimensionality) are easily understandable for the final user, in this case teachers. Besides, this is one representative paradigm in ML field [30].

## III. WIoTED System

Student engagement is generally considered the driving force of active learning [32] and can be viewed as active participation in the learning process that contributes to deeper and more meaningful learning.

Considering engagement as a key element for learning, the system developed is based on a participatory approach. By using active participatory methods, the students become active individuals; they are autonomous, more independent, co-participants in their own training, etc. In this case, the technology supports and guides them during the activities. The system is also based on student-centered learning [33], an approach involving an active learning style and the integration of learning tools according to the students' own learning progress. The WIoTED system supports collaborative learning. In order to carry out the main task, the student can work individually, coordinated by turns or in groups, depending on the nature of the learning activity. In this way, students can work productively with each other, develop collaborative skills and mutual help. The technology encourages students to explore the environment together with their peers and to communicate, coordinate, and collaborate with each other to achieve a common goal. WIoTED is an interactive and collaborative system designed to improve motivation and learning in primary and secondary schools based on our previous studies [32]. It integrates a new form of human–computer interaction. The students can interact with the educational system and the environment through everyday objects such as cards, toys, and coins (*smart objects*). At the same time, the system helps students and teachers send multisensory feedback through displays and a new *wearable device*. It is easy to use and offers students, mobility. The data collected in each class enable teachers to derive deeper insights from their classroom activities.

The system is composed of three main components: 1) the visualization board, which is the main screen (multimodal user interface) showing the educational task, activity, feedback, results, etc.; 2) unobtrusive wearable devices worn on the wrist; and 3) smart objects, which are common educational objects with integrated near field communication (NFC)


Fig. 2. WIoTED in a classroom, students play by turns.

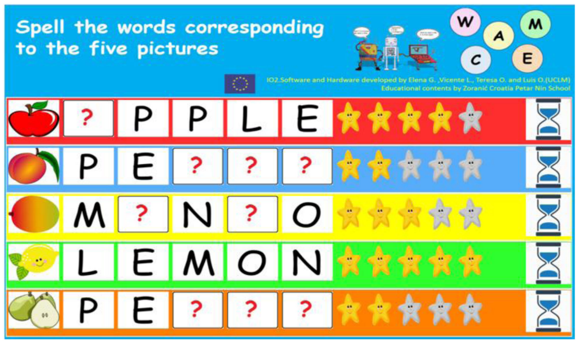


Fig. 3. Spelling game.

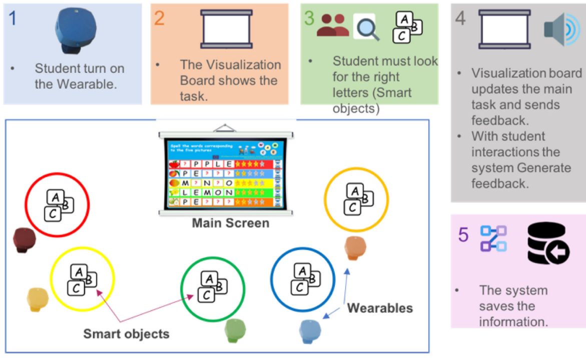


Fig. 4. WIoTED activity process.

sensors. In order to interact with the system, the students must look for the right educational smart object and bring it closer to the wearable device.

The functionality of the system is as follows. The educational task is projected on the wall using the *visualization board*. Students with tangible *smart objects*, i.e., the objects with integrated NFC tags, can interact with the main interface. This requires the wearable device incorporating the NFC reader to interact with the main interface, and thus, it is necessary to bring the objects closer to the *wearable device*. For example, if in the educational task an object must be associated with another, the student only has to bring the corresponding object closer to the *wearable device*, and the system recognizes it and displays the outcome of the learning activity. WIoTED deployed in a classroom can be seen in Fig. 2, with the three main components.

We developed WIoTED using JavaScript in the environment Node.js [34] and HTML5 for the interfaces. We use the WebSocket [35] protocol for interconnecting all devices. As a database, we use MySQL [36]. The *wearable device* was developed with System on a Chip ESP8266 [37] equipped with WIFI connectivity and an NFC reader connected to it.

### *A. Educational Task Sample*

WIoTED allows students to engage in diverse learning activities included in the task-based learning approach. In these activities, in order to successfully complete the task, the students have to look for the correct intelligent objects so that they complete their part of solving the main task. Some examples of the tasks WIoTED offers are association of colors to objects, identification of cities belonging to various countries, grouping numbers according to determined conditions and characteristics, etc.

A sample activity is the "spelling game" (see Fig. 3), a collaborative learning game developed for learning foreign languages. Spelling is an activity focused on improving reading and writing in a foreign language. The students acquire habits and routines to learn the letters that make up words [38].

The activity process is as follows (see Fig. 4). First, the student must turn on the *wearable device* in order to connect with the system. The *visualization board* shows the main task. A collection of pictures is displayed. Each picture has the number of letters that the student has to complete to spell the image in English.

The student must look for the right letters (smart objects) and associate them with the given picture. In order to interact with the system, the students bring the smart object closer to the wearable device. For example, the students must find the letters that form the name of the fruit in English (see the example in Fig. 3): A-P-P-L-E for a student in the red team or M-E-L-O-N for other student in the yellow team.

At the same time, the visualization board updates the main task and sends feedback.

Depending on the letter found, the feedback can be right, duplicate, or wrong.

The system saves the information and, in real time, the teacher can analyze the students' results.

For the purpose of this article, students played in groups of five, with everyone from a different team identified by a color. For example, in Fig. 3, the spelling problem "A-P-P-L-E" was solved by a single student, but the activity is collaborative because the five students from the five different teams need to solve their "panel." This is because to complete the activity, it is a requirement that all groups finish it, and is the condition to continue with the next task.

## IV. Materials and Methods

In this section, we present the process of data capture, analysis, classification, and application of MMLAs using the WIoTED system. The main objective of this method is twofold. To evaluate the WIoTED system during an academic year, obtaining relevant data and providing useful methods/tools to increase student engagement in class and to answer the research question: Can the WIoTED system provide information about student engagement using MMLAs methods?

In order to use the proposed methodology in a real educational context, we can differentiate four stages of data capture and automatic analysis development, with the consequent technological system and architectures (see Fig. 5). The first stage sets the device and software architecture necessary to capture the learners' interaction with the educational system (WIoTED) (data capture). The second establishes a web service to receive, categorize, and store data (data collection). The third stage identifies students' behavior patterns and proposes a novel student engagement classification in relation to the data captured in the previous stage (analysis and classification). In order to obtain key data in this stage, the students should have used the system during a complete academic year. The fourth stage is related to results (see Section V). It presents graphical visualizations about the students' behavior and engagement classifications to help teachers make decisions in the classroom (teacher analytics). Fig. 5 shows the LAs process using WIoTED, which is explained in the following sections.

### A. Participants and Learning Activity

A total of 18 students aged 13–15 years, with a mean age of $14 \pm 0.76$, took part in the study: 12 boys (67%) and six girls (33%). They were recruited as participants of this study when they were in their first year at a Spanish secondary school. Three of their teachers collaborated in the study.

These students participated in a one-year (one-semester as we do not include the holiday months) participatory learning program aimed at developing foreign language skills. The prolonged process of this program provided sufficient time for the students to become familiar with the technology.

The learning activity in the article consisted of activities to learn English as a foreign language. Each learner wore the wearable device on their wrist and interacted with the smart objects. In order to analyze the captured data while learners were using the WIoTED system, we organized groups of five students. All five students were doing their task at the same time to complete an activity. However, to complete the main goal of the task, the students had to work in groups. Throughout the course, in a series of sessions, 18 different students performed tasks, on average 21 tasks per student. Task were assigned by turns.

Bearing in mind that the main objective of the educational activity was to learn English, the students carried out spelling activities. It has been used to explain the process of data capture, because the students preferred this type of activity and repeated them in all the classes. However, in each session, new and increasingly complex educational content was added, with the difficulty of the tasks increasing. We also included associating English words with objects (smart objects).

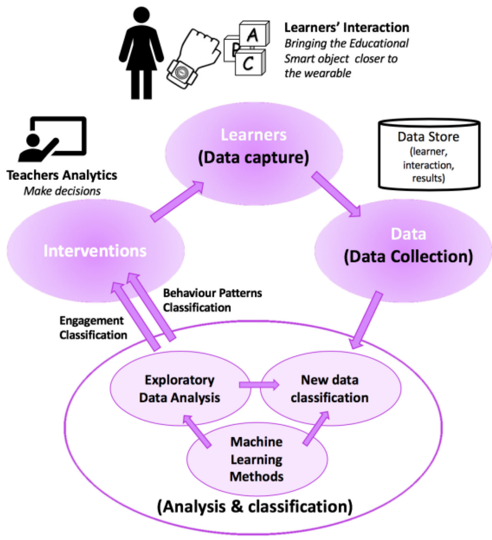


Fig. 5. LAs process using the WIoTED system.

The process was as follows. The teacher explained the activity, and subsequently, the students carried out the task through the WIoTED system. In order to carry out the data capture stage, on one hand, the system captured students' interactions, and on the other hand, the teachers used the direct observation method [39], i.e., they observed the students' progress and took notes about everything happening during the class. The purpose of this method, widely used by the human–computer interaction community, was to collect information allowing the evaluator to assess the subjects without altering the environment. At the end of the session, data obtained by the system were compared and validated with teachers' notes. In this way, we classified behavior patterns related to engagement.

### B. First Stage: Data Capture

In the first stage, data capture, the software of the wearable device identifies the type of interaction. If it recognizes that it is correct, the data are sent to the second stage; otherwise, it eliminates the incorrect data. These eliminations are required to avoid saturating the system with data that do not provide information. The environment works with events so that each student interaction (bringing educational *Smart objects* closer to the *wearable device*) generates a series of internal messages with associated information. This information is composed of, among other elements, the results of the task (right, wrong, or duplicate), which object has been selected, the learner, time, etc.

TABLE I
DATA CAPTURED LOG

| Date | Time | Origin | Type/Action | Received Data | Result |
|---|---|---|---|---|---|
| 31-oct | 09:29:47 | Teacher | Control | Start task Spell3 | |
| 31-oct | 09:29:51 | Student_Red | Interact | T | Right |
| 31-oct | 09:31:28 | Student_Red | Interact | E | Wrong |
| 31-oct | 09:31:39 | Student_Red | Interact | H | Right |
| 31-oct | 09:31:40 | Student_Green | Interact | A | Wrong |
| 31-oct | 09:31:40 | Student_Red | Interact | H | Duplicate |
| 31-oct | 09:31:43 | Student_Green | Interact | B | Wrong |
| 31-oct | 09:31:46 | Student_Green | Interact | C | Wrong |
| ... | ... | ... | ... | ... | ... |
| 31-oct | 09:34:01 | Student_Blue | | | Right |
| 31-oct | 09:34:01 | System | Control | Task over Spell3 | |
| 31-oct | 09:34:02 | Student_Yellow | Interact | A | |
| 31-oct | 09:34:46 | Student_Green | Interact | J | |
| 31-oct | 09:35:50 | Teacher | Control | Start task Spell10 | |

### *C. Second Stage: Data Collection/Labeling*

The second stage, through a web service, captures and stores the events received in the classroom, generating a log of events. It also processes the log of events to give these events a semantic meaning.

We used WebSocket, JavaScript, and MySQL technologies to enable communication between the interaction capture model and the stored learning record. This provides the ability to save all the data generated by an interaction in a database that is subsequently accessible for analytics purposes. The next variable is the collection of data and at the same time the input for the analysis stage. The structure of the data captured and stored in the event log is given in Table I. The following columns are stored in this log.

1) *Date*: Date of the lesson, corresponding to the date on which the WIoTED activity is carried out.
2) *Time*: Time of each event and users' interaction.
3) *Origin*: The person who triggers the event. In this case, the students, the teacher or the system.
4) *Type/Action*: The type of user interaction. There are two types: teachers'/system's actions are the interaction related to controlling or coordinating the educational task. Students' actions include every interaction carried out by the students to complete the tasks.
5) *Received Data*: Information received at the event in the following.
a) *Start Task*: Name of the task that the teacher has initiated.
b) *Task Over*: The system detects that all students have completed a task.
6) *Value*: A student's interaction data. When the students interact with the task, there are three types of answer as follows.
a) *Right*: It means that the interaction carried out by the student is correct. For example, if the student has to spell the word "H-O-U-S-E" and she/he interacts with a smart object whose content is the letter "H," the result is correct.
b) *Wrong*: It means that the interaction carried out by the student is incorrect. For example, if the student has to spell the word "H-O-U-S-E" and she/he interacts with a smart object whose content is the letter "P," the result is incorrect.
c) *Duplicate*: It means that the interaction carried out by the student is duplicated. For example, if the student has to spell the word "house" and she/he interacts with a smart object whose content is the letter "H" and in a previous interaction, she/he already interacted with same letter "H," the result is duplicated.

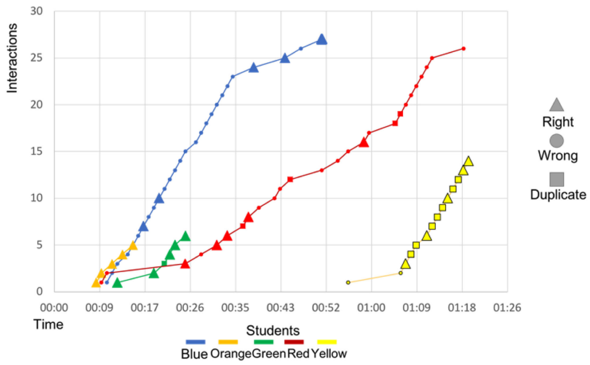


Fig. 6. Student interactions.

### *D. Third Stage: Analysis and Classifications*

The third stage allows the analysis of the stored learning records in two senses. First, it is intended to identify the most necessary variables in the data, then we apply EDA [40] to summarize their main characteristics and classify the different behavior patterns of the students while using the WIoTED system. Second, we use ML methods to identify the students' engagement in the learning activities.

EDA is an approach to analyze data and summarize their main characteristics, often with visual methods, which gives us a better understanding of the data. Several visualization methods can be used for this purpose, such as histograms, scatter plots, heat maps, and box plots.

Sample EDA: For each task, we propose a graphical representation of the students' interactions over time. This graph shows the interactions as wrong, right, or duplicate. In Fig. 6, we can see a representation of these data for one task. For each student, indicated by a color, we represent on the $x$-axis the moment at which she/he executes an interaction and, on the $y$-axis, the number of the interaction within the task.

We represent the right answers with a triangle, the duplicate answers with a square, and the wrong answers with a circle.

This graphical representation allows us to analyze a series of possible behavior patterns. For instance, in Fig. 6, we can see how four students (orange, blue, green, and red) start the interaction around 10 s after the game starts. These data help us to determine whether students pay attention to the task. We call these data start interaction.

Analyzing all the data captured throughout the experiment and representing the start interaction in a box-and-whisker plot (see Fig. 7), we can see how most students' start interaction around is located at around second 8, the median, with an interquartile range of 12 ranging from 4 to 16 s. These data correspond to the reaction time that the students need to start the educational task, i.e., to think about the answer and begin to respond. A time very close to zero could mean that the student

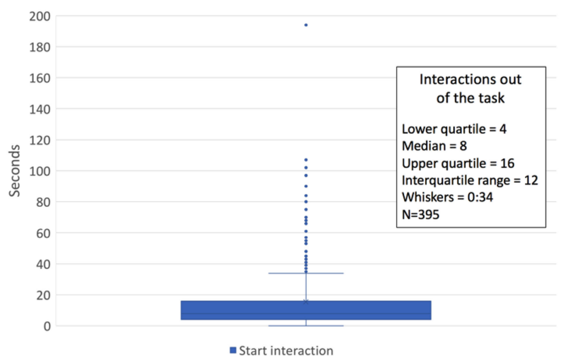


Fig. 7. Start interaction box-and-whisker plot.

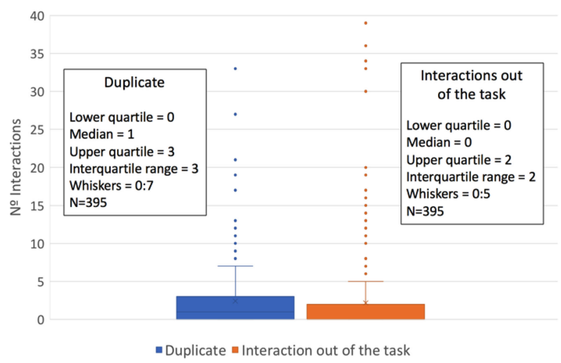


Fig. 8. Box-and-whiskers plot of duplicates and interactions outside the task.

has not thought about the response, starting to respond randomly, and very high reaction times may indicate that the student is distracted and is not aware of the start of the task [41]. In Fig. 6, we can also see how the student represented by red completes the task at second 58 (all answers right). However, she/he continues interacting with the system until the yellow student completes the task. In this case, the student is not aware of the task progress, i.e., she/he is not paying attention.

In Fig. 8, using a box-and-whisker plot, we represent all the experimental data about the number of interactions that the students carry out after having completed their task; we call this variable interaction outside the task. We can see that most of the students do not perform interactions after completing their task, they are focused on the activity. We obtain a median of 0, with an interquartile range of 2 ranging from 0 to 2 interactions.

In the graphical representation (see Fig. 6), taking into account the yellow student's interactions, we observe an atypical value of start interaction, 55 s. Moreover, around 50% of his/her interactions are duplicate. A duplicate answer means right answer repetition. Many duplicate responses may indicate that a student is not aware of the results of the task. To establish an acceptable number of duplicate responses, we have represented the number of duplicate responses throughout the experiment in a box-and-whisker plot (see Fig. 8). In our study, each task has five right interactions, a number greater than two duplicates could indicate that a student is not aware of the outcome of their interactions.

The new selected variables after having carried out the EDA are the following.

1) *Task Time*: This variable refers to the total time of the task in seconds. It describes the time from the moment the task starts until all the students finish it.
2) *Start Interaction*: This variable means the initial time at which a student starts the interaction with the educational task. This is measured in seconds.
3) *Task Over Time*: Interval of time in seconds that passes from the student's first interaction to their last.
4) *Interaction Out of the Task*: This variable defines the number of interactions that the student carries out after finding the right answers and therefore completes the task. These may be because the student is distracted and generally not paying attention in class.

## V. Results

In this section, we present the results obtained during a set of trials conducted in a Spanish secondary school, Albacete, Spain. The main objective is to gain a better understanding of the engagement progress in a long-term participatory learning context using IoT and wearable technologies and to capture relevant information on the progress of a class session. That is, we have attempted to investigate the students' interactions and behaviors during a one-year course of learning. The captured data have been analyzed to build the new engagement classification model.

### A. Behavior Patterns

This classification into groups depending on the students' interaction behavior patterns provides us with a first understanding of the behaviors. Hence, we can create a taxonomy of students' behaviors related to the concentration of interaction. We especially focus on metrics that other research works have used to obtain information about motivation, described in Section II. These are attention, curiosity, challenge, control or confidence, and relevance.

*1) Attention*: It refers to learners' interest. It is critical to capture and maintain learners' interest and attention.

*2) Curiosity and Challenge*: According to [15], computer activities that provide a challenge and trigger students' curiosity are intrinsically motivating.

*3) Control or Confidence*: Individuals should have opportunities to make choices about the process, the use of the system and their interactions with it. Providing choice within a digital activity potentially enhances students' perception of autonomy, thus increasing user motivation. This component focuses on developing expectation of success among learners, and how such expectation allows learners to control their learning processes.

*4) Relevance*: This measures whether the students are familiar with the material and relate to it. It can be relevant in two ways. The students know the educational content, or they do not know the content but are interested and would like to learn (trial and error method).

TABLE II
BEHAVIOR PATTERNS CLASSIFICATION

| | Date | Game | Task time | Student | Duplicate | Right | Wrong | Start interaction | Task Time | Interaction out of the task | Task over time |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 31-oct | Spell | 119 | Student_Blue | 2 | 5 | 0 | 24 | 46 | 0 | 0 |
| 2 | 31-oct | Spell | 119 | Student_Green | 3 | 5 | 10 | 11 | 49 | 0 | 0 |
| 3 | 31-oct | Spell | 119 | Student_Orange | 0 | 5 | 3 | 30 | 66 | 0 | 0 |
| 4 | 31-oct | Spell | 119 | Student_Red | 1 | 5 | 0 | 61 | 106 | 1 | 1 |
| 5 | 31-oct | Spell | 119 | Student_Yellow | 0 | 5 | 0 | 102 | 119 | 0 | 0 |
| 6 | 31-oct | Spell | 119 | Student_Orange | 1 | 5 | 15 | 10 | 35 | 0 | 0 |
| 7 | 31-oct | Spell2 | 103 | Student_Blue | 1 | 5 | 14 | 26 | 81 | 1 | 3 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

Taking into account these variables in the EDA and the results of the direct observation, we analyzed the data and proposed the following classification.

1) Students know the solution and are engaged in the task. This type of behavior exhibits the following characteristics:
   a) paying attention to the activity (ATTENTION);
   b) focused on doing the task (CURIOSITY);
   c) interacting correctly with the system (CONTROL);
   d) knowing the answers (RELEVANCE).
2) *Engaged Student*: This type of behavior presents the following characteristics:
   a) paying attention to the activity (ATTENTION);
   b) focused on doing the task (CURIOSITY);
   c) interacting correctly with the system (CONTROL);
   d) not knowing the answers, but using the trial and error method to learn and complete the task (RELEVANCE).
3) *Distracted Student*: This type of behavior exhibits the following characteristics:
   a) paying attention to the activity (at intervals) (ATTENTION);
   b) not focused on doing the task (CURIOSITY);
   c) random interactions with the system (CONTROL);
   d) not knowing the answers. (RELEVANCE).
4) *Distracted Student Not Likely to Learn*: This type of behavior presents the following characteristics:
   a) not paying attention to the activity (ATTENTION);
   b) not focused on doing the task (CURIOSITY);
   c) not interacting with the system (CONTROL);
   d) possibly knowing the answers (RELEVANCE).

Table II represents the four dimensions of the motivation, attention, curiosity or challenge, control or confidence, and relevance (1 being the highest; 0 being the lowest variables' perception).

The behavior patterns are represented through visual graphics in Fig. 9.

Fig. 9(a) shows an example of the behaviors corresponding to the type "students know the solution and are engaged in the task." It can be seen how the start time of the five students is a value that can be considered within the mean. They are focused on the task, not making mistakes and not interacting outside the task. They are paying attention to the task and are aware of task progress. That is, we can assume that the students are engaged.

Fig. 9(b) shows the behavior type "engaged student more likely to learn." This is associated with the trial-and-error method [18]. On one hand, the student starts interaction on time and is aware of task progress because she/he stops interacting with the system when the task is completed. On the other hand, it has a few duplicates and many wrong answers. This is because she/he does not know the answer, but tries to learn and solve the task (trial-and-error method). In this case, the student is engaged.

In Fig. 9(c), we can see the behavior type corresponding to the taxonomy "distracted student not likely to learn." This student has a low start interaction, many errors, and a high number of duplicates. She/he finishes the task but is unaware of the progress of the task. She/he interacts randomly without paying attention to the task.

In Fig. 9(d), we can see the behavior corresponding to the type "distracted student not likely to learn." In this case, the student has a high start interaction, i.e., she/he has been distracted but starts to interact because is alerted by the teacher and his/her classmates. She/he makes many duplicate and wrong answers. This student is not engaged.

### B. *Machine Learning Classification Models*

As indicated in Section II-B, we address the question of engagement in the students' learning process with respect to the proposed methodology, their behavior and interactions. In this particular experimental case, the class (label to predict) would be yes, if there is engagement or no, if there is none.

When applying ML techniques, it is necessary to have a training dataset available, and in our case, the data source comes from the recorded learning sessions previously reported. Throughout our experiment, data were captured. Every case/ instance in our dataset represents one task for a specific student, where particular features are recorded (see Table III). A total of 395 tasks were analyzed in the study. A new column has been added to this collection of features, indicating whether the student was engaged or not. The data were labeled using expert knowledge by observation. That is, we added the values for the class variable to our data captured by the WIoTED system. For every case, this class (or label) represents whether or not the students have shown engagement when performing the task. The collection of the features plus their classification label forms our training dataset to learn through representative ML algorithms. Thus, some specific classification models were learned and then validated.

The Waikato environment for knowledge analysis (WEKA) [42] was used to perform these learning and validation phases. Since we are interested in rule systems, thanks to the ease of their interpretation, we chose rule generators and decision trees, from which rules can be straightforwardly extracted.

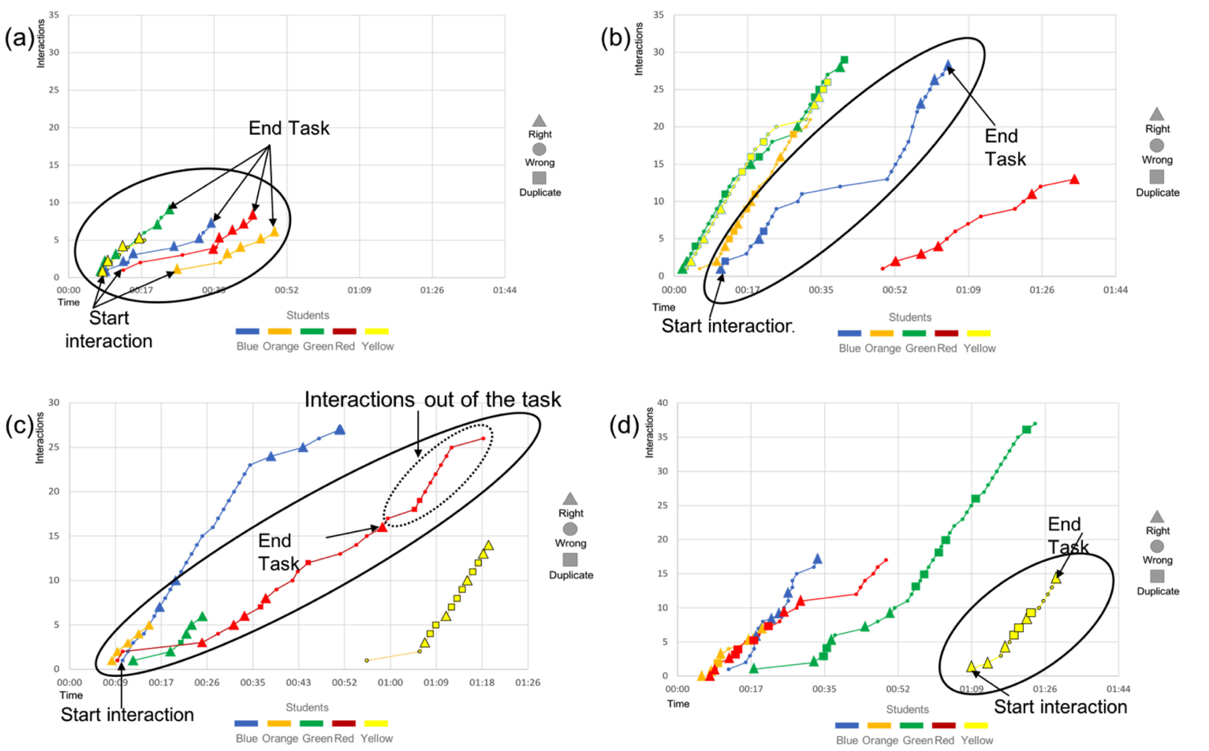


Fig. 9. Behavior patterns, graphical representation. (a) Students know the solution and are engaged in the task. (b) Engaged student is more likely to learn. (c) Distracted student not likely to learn. (d) Distracted student not likely to learn.

TABLE III
PROCESSED DATA

| | Attention | Curiosity/Challenge | Control/confidence | Relevance |
|---|---|---|---|---|
| BP1 | 1 | 1 | 1 | 1 |
| BP2 | 1 | 1 | 1 | 0,5 |
| BP3 | 0,5 | 0,5 | 0,5 | 0 |
| BP4 | 0 | 0 | 0 | 0 |

There exist multiple score metrics to validate the performance of a model. When the dataset is not highly imbalanced, the most accepted measure is accuracy, which refers to the percentage of correctly classified instances. In order to evaluate in an honest manner, the original dataset is divided into two splits: 1) train—used for learning the model; and 2) test—used to predict labels with the model learnt. Comparing, in the test set, the real label with the predicted one, accuracy is computed. When there is no high dimensionality in the dataset, $k$-folds cross-validation is usually preferred. In this case, the dataset is divided into $k$ folds, and the learning–validation process is repeated $k$ times. For each time, $k$-1 folds are used for training, and the remaining one is utilized for validation purposes, with all folds being used once as the test. The final measure value is given as an average, using the $k$ iterations.

As this problem is binary, per every case there are four possible scenarios, depending on the yes/no value for the real class, and the yes/no value for the predicted one. This is compactly shown in the confusion matrix, as we will see.

For rules, we applied OneR [43] and PART [44] algorithms, and, for decision trees, the J48 algorithm [45], which corresponds to the C4.5 algorithm, one of the most popular algorithms. The chosen algorithms provide classification and prediction and also intelligible output. This allows us to characterize the engagement in terms of the attributes generated from the processed data captured and see whether such data can be used for engagement prediction.

The OneR algorithm is typically selected as a baseline technique for generating rules in an ML problem. It returns very simple association rules, involving just one attribute in the condition part. In spite of its "simple philosophy," it works surprisingly well in practice with real-world data, as happens with our problem.

The results of applying the OneR rule algorithm generated by WEKA are summarized in Fig. 10. This classifier involves determining that there is engagement when the number of duplicates is lower than 3.5. Observing the confusion matrix, all the errors or misclassifications (63) are obtained in cases classified as nonengagement, which they in fact are. With only one rule, we obtained 84.05% of correctly classified instances, i.e., 15.95% are incorrectly classified. This represents very good values for a single rule algorithm.

Decision trees are an attractive option for classification. A decision tree is a collection of decision nodes, connected by branches, extending downward from the root node to leaf nodes. Beginning at the root node, attributes are tested at the

```
=== Classifier model (full training set) ===

duplicate:
  < 3.5   -> Yes
  >= 3.5  -> No

(332/395 instances correct)

Correctly Classified Instances    332   84.0506 %
Incorrectly Classified Instances   63   15.9494 %

=== Confusion Matrix ===

  a   b   <-- classified as
 96  63 |   a = No
  0 236 |   b = Yes
```

Fig. 10. WEKA OneR algorithm output.

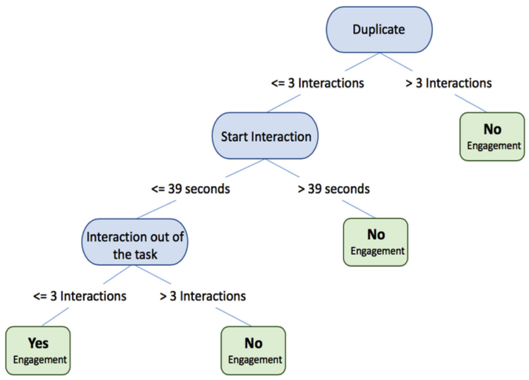


Fig. 11. WEKA J48 decision tree.

decision nodes, with each possible outcome resulting in a branch. Each branch then leads either to another decision node or to a terminating leaf node. From a decision tree, a system of rules is directly obtained. In Fig. 11, we show the output of the J48 algorithm in WEKA with tenfold cross validation. In this case, we obtained a decision tree with four levels and a tree size of seven. The percentage of correctly classified instances was 98.73%. Consequently, only 1.27% are incorrectly classified. This is a great improvement on the OneR algorithm; not only is it 14% more accurate in relative terms, but only a few errors (5) are obtained, which in this classification task could be considered significantly low. The graphical representation of the decision tree is depicted in Fig. 12. To classify any given new case, we have to start at the root level, if the attribute duplicate has a value greater than 3, we go to the right branch and the classification label will be No. Otherwise, we continue with the left branch and test the next decision node, in this case Start Interaction, and so on.

The final algorithm applied was PART. This belongs to the CN2 induction family, which are in fact learning algorithms for rule induction. In WEKA, PART is based on the same learning algorithm as J48, but the way rules are generated differs, as it permits the IF-ELSE format. Looking at the output (see Fig. 13), we can see how the rule system is totally compatible (or equivalent) with the one generated by J48, and the

```
J48 pruned tree
------------------

duplicate <= 3
|   startinteraction <= 39
|   |   interactionoutofthetask <= 3: Yes (241.0/5.0)
|   |   interactionoutofthetask > 3: No (24.0)
|   startinteraction > 39: No (34.0)
duplicate > 3: No (96.0)

Number of Leaves  :   4

Size of the tree :    7

Correctly Classified Instances     390   98.7342 %
Incorrectly Classified Instances     5    1.2658 %

=== Confusion Matrix ===
   a    b   <-- classified as
 154    5 |    a = No
   0  236 |    b = Yes
```

Fig. 12. WEKA J48 algorithm output.

```
PART decision list
------------------

duplicate <= 3 AND
startinteraction <= 39 AND
interactionoutofthetask <= 3: Yes (241.0/5.0)

: No (154.0)

Number of Rules  :   2

Correctly Classified Instances   390 98.7342  %
Incorrectly Classified Instances  5  1.2658  %

=== Confusion Matrix ===
   a    b   <-- classified as
 154    5 |    a = No
   0  239 |    b = Yes
```

Fig. 13. WEKA PART algorithm output.

classification metrics + confusion matrix also coincide. Thanks to a more compact syntax, in this case, only two rules are obtained:

IF duplicate $<$ 3 AND start interaction $<=$ 39 AND interactionofthetask $<=$ 3 THEN **Yes** OTHERWISE **No**.

When we analyze these results, we can observe how some attributes appear as significantly important and others are not. As we can observe, some of them are used in the rules' conditions and others are simply omitted or ignored when performing the classification processes. For this reason, we also studied the individual impact of every feature with respect to the class, in other words, the relevance of every measurable factor when observing engagement. To do so, we used a "correlation" measure known as information gain, which is actually based on conditional entropy. Information gain is a broadly accepted measure to rank attributes' importance.

We performed an analysis of these factors, using attribute selection tools provided by WEKA. Information gain given the class is computed for all the attributes. That is, this conditional entropy is measured for each attribute with respect to the classification variable. Values vary from 0 (no information) to 1 (maximum information). Those attributes that contribute more information will have a higher information gain value and have

```
=== Attribute Selection on all input data ===

Search Method:
  Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 9
classification):
  Information Gain Ranking Filter

Ranked attributes:
 0.4101   2 duplicate
 0.2342   7 interactionoutofthetask
 0.1621   5 endtasktime
 0.1414   6 startinteraction
 0.0896   8 taskovertime
 0.0555   1 tasktime
 0.0396   4 wrong
 0        3 right

Selected attributes: 2,7,5,6,8,1,4,3 : 8
```

Fig. 14. WEKA performed an analysis.

relevance in the classification, whereas those that do not add much information will have a lower score and may not be used in the classification, as they are not informative enough to determine the class label.

Fig. 14 shows the WEKA output of this analysis, where we can see the ranking of attributes according to their information gain. The attributes that contribute most information to the classification are *duplicate* and *interaction outside the task*, with 0.4101 and 0.2342, respectively. We can see how the interaction attribute *right* does not provide information, which is logical because it has a constant value of 5, the number of *right* interactions in each task of the article, so it is not discriminative for determining the class value. The number of *wrong* and *task time* interactions have low information gain value. These two values are not used in the PART rules or in the decision tree generated by WEKA. In these cases, the only attributes used are *duplicat*e, *interaction outside the task*, and s*tart interaction*.

In this section, we have seen how this problem can be validated by classification models, with our particular interest being in rules systems. The rules obtained not only seem reasonable to the experts but also provide high scores in terms of validation metrics. As some attributes were not present in the decision rules, we also ranked them with respect to their individual informative power to predict the class. Similarly, the obtained ranking coincides with the problem knowledge. Thus, we have proven how classification models provide a valid methodology to evaluate student engagement.

## VI. Discussion

To answer our research question: Can the WIoTED proposal provide information about student engagement using MMLAs methods? We propose that our findings provide information about student engagement and disengagement. In addition, the proposal offers relevant information about the behavior student and their progress in the class.

During the article, EDA, direct observation and ML methods were applied. The results obtained with all these methods were compared and found to be very similar. However, the exploratory analysis offers more accurate information about users' behavior and progress than direct observation. This is because the taxonomy created on students' behavior proved useful and easy to understand by the teachers who participated. The behavior taxonomy and visualization is a valuable tool for teachers, who will be able to personalize learning and improve the teaching environment [10].

ML techniques are a powerful tool that allows us to predict student engagement, the pattern of behavior, and even key student progress variables for performing diagnosis automatically. We evaluated several ML techniques using the direct observation values of the professors and the exploratory analysis (attributes and taxonomy). The ML techniques evaluated yielded similar results. The information gain analysis shows the greater weight of the duplicate and interaction outside task attributes. The task time attribute has a low information gain in contrast to that observed in [41]. This is due to the greater number of different attributes that our system evaluates.

The results of applying ML techniques allows us to notify the teacher about the students who are disengaged. In order to know the reason of the disengagement, exploratory analysis and behavioral taxonomy, provide more specific information. Offering student progress, during the class, allowing the teacher to detect if the learning content level is high, they are bored, need help in some aspect, etc.

## VII. Conclusion

This article has presented the WIoTED system. It is an interactive, collaborative system designed to improve motivation and learning in primary and secondary schools. To interact with the system and carry out the learning task, the students must bring educational smart objects (NFC tag inside) closer to the wearable devices. At the same time, the system updates the visualization board and sends feedback and results. While the students carry out the task, the system captures all the data. In this article, we show the possibility of measuring student engagement over time and learners' interactions using the WIoTED system, combining MMLAs and ML techniques to identify students' behavior and engagement.

LAs research has traditionally focused primarily on computing contexts, ignoring real-world environments because of the complexity of capturing data in them. Currently, researchers are focusing their efforts on how to automatically collect information from real-world learning contexts, making face-to-face conference analysis as feasible as massive open online course (MOOC) session analysis. The results obtained show that the WIoTED system is an efficient tool to carry out MMLAs in a real-world learning context. The students can interact with the educational system and the environment through the wearables and smart objects. The number and timing of interactions carried out by the student through the wearable devices offers information that can be used in a MMLAs process. We have achieved a better understanding of the progress of engagement in a context of long-term participatory learning using IoT and wearable technologies.

We analyzed a total of 395 tasks carried out by 18 students. By applying the ML techniques, we obtained good results, meaning we can state our goals were satisfactorily achieved using the captured data. Nonetheless, we think that extending the study with a larger number of students and tasks would give us a more extensive taxonomy and allow us to use more labels to characterize the students' behavior.

The WIoTED system can be used in various types of activities, but in the current study, only the spelling activity was performed. This type of activity has many learning benefits [38] and has served us for the purposes of the study. However, we think that in the future we should carry out similar studies with other types of activity, allowing us to extend the taxonomy of behaviors.

Various works have used multimodal ML [27] and included devices, such as cameras, sensors, accelerometers in wearable, and GPS. We consider that the incorporation of these devices to the WIoTED system would offer more accurate and relevant information about the classes and students' behavior, enhancing the study we have conducted.

In this article, we can see that active participatory methods, and collaborative and student-centered learning can have a tremendous impact on pupils, combined with novel and friendly technologies, with all these providing alternatives for student learning.

For future work, we would like to include the teacher's tools, using ML techniques in real time and showing the behavior results while using WIoTED. During the long-term study, teachers used the direct observation method [39]. At the end of each session, data obtained by the system were compared and validated with teachers' notes. In this way, we classified behavior patterns related to engagement, and at the same time, the results were validated by the teachers. It would be interesting for teachers to use the system in class, the taxonomy, the data obtained, and ML techniques. In this way, we could know the teacher's perception as well as the students' progress. Our system will help teachers to assess students' motivation and make decisions to engage students in the learning progress and to tackle the problem of dropout. By using our system, teachers can have quick feedback, so that, during the learning process, they are aware of which students present problems of disengagement. If this diagnosis is made in time, which the solution proposed in this article facilitates, they may be able to reformulate the teaching strategy with the aim of fostering the involvement of those specific students

### VIII. Ethics

In no case did the captured data store students' personal information. The data were depersonalized and all student interactions were anonymized. We received official authorization to carry out this investigation. Both the school's head teacher and the school council gave permission to conduct our experiment.

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CAPÍTULO 3

# Discusión

En este capítulo se presenta la discusión general sobre la investigación realizada en esta tesis.

## 3.1 Discusión

Para abordar la investigación propuesta, se establecieron tres objetivos generales, y seis cuestiones de investigación. En los trabajos de investigación realizados en las publicaciones que forman el compendio, se ha dado completitud a los objetivos planteados y a las cuestiones de investigación planteadas.

### 3.1.1 Sobre el Objetivo 1

El primer objetivo plantea el estudio de los beneficios que el uso de las tecnologías *IoT y Wearable* proporcionan en la realización de actividades educativas basadas en tareas. Este estudio comienza con el análisis de los beneficios potenciales del uso de las tecnologías *IoT y Wearable*, en el ámbito del aprendizaje de idiomas basado en tareas, y centrados en alumnos de educación primaria. Se ha realizado con los educadores un análisis de esta metodología de enseñanza y su aplicación con las tecnologías *IoT y Wearable*, prestando especial atención a las dificultades de introducirla en las actividades educativas. Se han identificado las áreas en las que el uso de las tecnologías *IoT y Wearable* pueden tener más impacto. Con esta información se diseño, y se puso en marcha un prototipo de la plataforma educativa *IoT y*

*Wearable*. Esta plataforma fue evaluada en un entorno real con profesores y alumnos. La evaluación comprendió un análisis comparativo entre la realización de actividades basadas en tareas con la plataforma y la realización de actividades de forma tradicional. En base a los datos recogidos durante las pruebas, se identificaron una serie de áreas en las hay beneficios en uso de las tecnologías *IoT y Wearable*.

Una plataforma de estas características permite realizar actividades en la que los alumnos se pueden mover por al aula. El uso de los dispositivos *wearables* y del IoT ha demostrado ser una forma atractiva de interactuar con la plataforma desde cualquier lugar del aula, los alumnos se sienten cómodos moviéndose por el aula mientras realizan la tarea. La utilización de una pantalla general de visualización también se muestra como un medio excelente para mantener a todos los alumnos informados sobre el desarrollo de las tareas que se estaban realizando. Sobre objetos inteligentes se observa que prefieren objetos inteligentes tangibles frente a fichas inteligentes, lo que confirma que los alumnos prefieren trabajar con objetos reales [11]. Estas tecnologías han demostrado que permiten recrear escenarios familiares para los alumnos como el descrito por C. J. Hooperen et al. [24].

La plataforma permite guiar de forma autónoma a los alumnos en las acciones que deben realizar, el profesor puede centrarse en estimular a los alumnos a participar y en ayudarles con las dificultades que se les presenten. Los alumnos reciben un feedback continuo e inmediato tanto de la plataforma como del profesor. Uno de los principales problemas que ha impedido la amplia implantación del aprendizaje basado en tareas es el número de alumnos que participan. Los estudios han demostrado que las clases más pequeñas hacen que los alumnos reciban más atención individual de los profesores y tengan interacciones más activas con ellos [6]. A partir de los resultados del estudio, y los comentarios de los educadores, se ha comprobado que el uso de las tecnologías *IoT y Wearable* libera al educador de mucha carga de trabajo, incluso de tener que coordinar cada movimiento en las actividades. De todo ello, se concluye, que el uso de las tecnologías propuestas facilita el aumento del número de alumnos que puedan participar en las actividades.

El análisis de los datos captados a través de la plataforma se muestra como una fuente de información muy valiosa de manera similar a los hallazgos mostrados en [30]. A partir de la información obtenida, los educadores pueden evaluar el nivel de motivación y el progreso de cada alumno, así como la eficacia del enfoque de enseñanza utilizando esta plataforma. Basándose en el análisis de los datos captados, los educadores pueden planificar otras actividades para abordar las necesidades detectadas, como por ejemplo reforzar la participación de algunos alumnos, repasar vocabulario específico, principios gramaticales, etc

Se ha realizado una evaluación de la usabilidad de la plataforma al final de cada sesión. Los profesores rellenaron un cuestionario de la Escala de Usabilidad del Sistema (SUS). La plataforma propuesta ha obtenido una puntuación de 81,25 (sobre 100), lo que indica que los profesores tuvieron una opinión muy positiva de la misma.

El estudio ha permitido conocer mejor las características y necesidades de los usuarios finales. Una de las principales cuestiones que había que abordar es la relacionada con las interacciones que tienen lugar en una actividad basada en tareas y, por tanto, las características que se requieren de los *wearables* y los dispositivos IoT. Del análisis del material de vídeo que se grabó durante las sesiones, se desprende que es necesario maximizar la simplicidad de las interfaces, utilización del sistema y los mecanismos de interacción. El uso de interfaces sofisticadas o mecanismos de interacción que requieran mucha atención, puede distraer a los alumnos, lo cual es un problema relevante cuando se trata de niños pequeños [23].

Se ha demostrado que para la recolección de datos sobre cómo los alumnos desarrollan las actividades, el uso de la tecnología *IoT y Wearable* es muy adecuada [8]. Sin embargo, dada la gran cantidad de datos que la plataforma puede capturar, la plataforma debe incorporar mecanismos amigables de tratamiento de los datos para la preparación de informes por parte de los educadores.

### 3.1.2 Sobre el Objetivo 2

De los resultados y lecciones aprendidas en el primer estudio surge el segundo objetivo de esta tesis, ampliar el diseño de la plataforma *IoT y Wearable* para poder ser utilizada como una plataforma global de enseñanza. Este objetivo consta de dos subjetivos, el primero, la propia ampliación y mejora de la plataforma. El segundo, el desarrollo de un dispositivo weareable para interactuar con la plataforma que mejore la experiencia de usuario.

La ampliación del diseño de la plataforma y el desarrollo del dispositivo *wearable* se centran en cumplir los nuevos requerimientos observados en las evaluaciones, y que resultan claves para la aceptación de la plataforma por los usuarios finales. Una de las mejoras más significativas ha sido la simplificación de las interfaces, sobre todo del nuevo dispositivo *wearable*. En las evaluaciones realizadas para validar el diseño, se ha observado que los participantes se centraban más en la actividad sin requerir apenas atención al nuevo dispositivo *wearable*.

Siguiendo las tendencias actuales, el dispositivo *wearable* se ha desarrollado utilizando dispositivos electrónicos de código abierto [15]. Se ha prestado especial atención a la utilización de componentes de bajo consumo para que en la utilización de la plataforma durante una jornada, los educadores no deban tener que prestar atención a la recarga de las baterías del dispositivo. Esta característica es especialmente relevante ya que el número de dispositivos desplegados puede aumentar en función del tamaño de la clase. En este sentido, en un despliegue real de la plataforma, incluir en el dispositivo la posibilidad de carga inalámbrica podría resultar beneficioso al permitir cargar fácilmente los dispositivos.

En cuanto a los componentes físicos y sensoriales integrados en el *wearable*, se han basado en los comentarios de los usuarios finales en las pruebas de validación del diseño. Partiendo de un diseño inicial de dispositivo *wearable*, se observó que los usuarios realizaban un número significativo de intentos repetidos de interacción. La adición de mecanismos de retroalimentación háptica y visual, ha dado lugar a una versión mejorada del dispositivo en la que los usuarios son más conscientes de que han realizado una interacción. Los alumnos se han mostrado más cómodos utilizando el rediseño del dispositivo *wearable*, y se produce una reducción significativa del número de intentos de interacción. Con esta modificación de diseño se logra también una reducción significativa del consumo de energía. Con esto, se han podido comprobar los beneficios de contar con la participación de los usuarios finales en los procesos de diseño y prueba de concepto de un sistema.

Para la validación de la ampliación de la plataforma *IoT y Wearable* se han realizado una serie de evaluaciones en la que han participado alumnos y educadores que van desde el nivel de educación infantil hasta el universitario. En todos los niveles los usuarios han destacado el uso del dispositivo *wearable* como un sistema de interacción natural y amigable. Los educadores han valorado positivamente el seguimiento de la participación de los alumnos en las actividades que la plataforma permite. Algunos educadores han sugerido que la inclusión de mecanismos de detección de movimiento en el dispositivo *wearable* puede resultar útil para actividades de desarrollo de habilidades locomotoras en alumnos pequeños. En evaluaciones realizadas al margen del objeto de esta tesis, la plataforma ha presentado un uso potencial en otros ámbitos. En el marco de la Industria 4.0 [35] puede ser útil para actividades de formación de trabajadores. En el ámbito de las terapias cognitivas, algunos resultados iniciales han demostrado el gran potencial que puede tener esta tecnología para terapias con personas mayores [17] o discapacitadas. También se han realizado un estudio sobre ayudar a personas mayores que viven solas mediante esta tecnología [16].

### 3.1.3 Sobre el Objetivo 3

El tercer objetivo se centra en cómo procesar los datos que la plataforma captura en cada actividad, y si con estos es posible determinar el nivel de motivación de los alumnos. En los estudios realizados en los objetivos previos, los educadores, al analizar los datos después de cada sesión, han resaltado el gran potencial que éstos tienen para determinar los niveles de motivación de los alumnos. De la revisión bibliográfica se ha extraído que este objetivo se puede alcanzar aplicando técnicas de *Learning analitics* y *Machine learning* sobre los datos capturados. Tradicionalmente, la utilización de *Learning Analytics* se ha centrado principalmente en contextos informáticos, ignorando los entornos del mundo real debido a la complejidad de capturar datos en ellos. Actualmente, los investigadores están centrando sus esfuerzos en cómo recopilar automáticamente información de contextos de aprendizaje del mundo real. En este sentido, la plataforma y su capacidad para capturar datos de las interacciones de los alumnos la hacen adecuada para aplicar *Learning Analytics*.

Para realizar este tercer objetivo se ha planteado, por un lado, crear una clasificación de patrones de comportamiento de los alumnos mientras interactúan con la plataforma, y, por otro lado, crear un modelo que relacione los patrones de comportamiento con la motivación de los alumnos utilizando métodos de aprendizaje automático. Durante este objetivo se ha realizado una evaluación a largo plazo durante un curso escolar con un grupo de alumnos de secundaria. En las sesiones con la plataforma se aplicaron los métodos de análisis exploratorio de datos [41] y de observación directa [33] para determinar la motivación de los alumnos. Los resultados obtenidos con estos métodos se compararon y resultaron ser muy similares. Sin embargo, el análisis exploratorio ofrece información más precisa sobre el comportamiento y el progreso de los alumnos que la observación directa. El análisis exploratorio ha permitido crear una taxonomía sobre el comportamiento de los alumnos, y un conjunto de atributos que definen la forma con que los alumnos interaccionan con la plataforma al realizar una actividad. Los educadores destacaron que tanto la taxonomía como el conjunto de atributos resultaban útiles y fáciles de entender.

La utilización de las técnicas de ML se ha mostrado como una herramienta adecuada para obtener un modelo que permita medir la motivación de los alumnos, sus patrones de comportamiento, e incluso los atributos de interacción clave. Se han evaluado varias técnicas de ML basadas en aprendizaje supervisado, utilizando los atributos de interacción como valores de entrada y la taxonomía creada con el análisis exploratorio para etiquetar. Las técnicas de ML evaluadas arrojaron resultados muy positivos que han permitido obtener un modelo que permite clasificar a los alumnos con una precisión del 98,7%. Se aplicó también un análisis de ganancia de información sobre los atributos de interacción que muestra qué atributos tienen mayor peso en la determinación del patrón de comportamiento. Con el modelo obtenido, la plataforma *IoT y Wearable* puede informar a los educadores sobre la motivación de los alumnos, esto permite detectar cuáles no están motivados, o desvinculados de la actividad. Esto también va a permitir al educador tomar las medidas oportunas para volver a motivar a los alumnos en la actividad.

CAPÍTULO 4

# Conclusiones y Perspectiva Futura

El cierre de la tesis doctoral se detalla en este capítulo, dedicado a resumir las principales conclusiones obtenidas, y a presentar una propuesta sobre la perspectivas de futuro de esta investigación.

## 4.1 Conclusiones

Esta tesis se ha centrado en estudiar cómo el uso de las TIC, específicamente las tecnologías *IoT y Wearable*, pueden contribuir a reducir los niveles de abandono escolar temprano a través de mejorar los niveles de motivación de los alumnos. Se ha realizado un amplio estudio bibliográfico sobre cómo las tecnologías *IoT y Wearable* pueden aumentar la motivación de los alumnos. En las evaluaciones realizadas ha quedado confirmado que el uso de estas tecnologías genera en los alumnos motivación intrínseca. Además, estas evaluaciones permiten recolectar una gran cantidad de datos sobre cómo los alumnos realizan las actividades. Estos datos tratados bajo el enfoque de las metodologías *Learning Analytics*, proveen información a los educadores sobre el nivel de motivación de los alumnos. Con esta información los educadores pueden tomar medidas para evitar la desmotivación de los alumnos en la escuela y por tanto prevenir el abandono escolar. A continuación, se presentan las principales conclusiones que se han obtenido en esta tesis.

- Diseño hardware y software de la plataforma educativa.

Con la participación de profesores de educación primaria y secundaria se ha realizado un estudio sobre cómo introducir las tecnologías *IoT y Wearable* en las actividades educativas. Con esta información se ha diseñado una plataforma educativa basada en una interfaz humana tangible, con un mecanismo de interacción intuitivo a través de dispositivos *wearables*. Esta plataforma es un sistema interactivo y colaborativo diseñado para mejorar la motivación y el aprendizaje. Se ha validado el diseño a través de múltiples evaluaciones con alumnos de todas las edades y niveles en las que han realizado diferentes actividades relacionadas con lenguas extranjeras, geografía, matemáticas, ortografía, etc. Con los resultados de todas las evaluaciones y los comentarios de los usuarios finales, se ha ido mejorando e incorporando nuevas características a la plataforma. Ésta se ha desarrollando utilizando tecnologías ya disponibles, como NFC, WiFi, *WebSocket*, *JavaScript* y aplicaciones web en la nube. También se ha desarrollado un nuevo dispositivo *wearable* específico para la plataforma, con la finalidad de simplificar las interacciones de los usuarios. Esta basado en un microcontrolador SoC, integra un lector NFC, dispone de conectividad WiFi, y una interfaz visual y háptica. El desarrollo de la plataforma y el dispositivo *wearable* se ha realizado en un continuo ciclo de desarrollo y ha mostrado, como una de sus características más destacables, su capacidad de actualización y ampliación.

- Diseño del sistema de captura y análisis de datos.

Integrado en la plataforma, se ha desarrollado un sistema para la captura de los datos que generan los alumnos con sus interacciones mientras realizan las actividades. Con estos datos, y aplicando el enfoque *Learning Analytics*, se ha podido extraer una taxonomía de patrones de comportamiento relacionada con la motivación de los alumnos. Con esta taxonomía, los datos de interacción y aplicando técnicas de Machine Learning, se ha creado un modelo que permite en tiempo real informar a los educadores sobre el nivel de motivación de los alumnos durante las actividades. Para obtener la taxonomía y el modelo se han realizado cerca de 400 actividades diferentes por 18 alumnos del colegio Diocesano de Albacete, en un estudio a largo plazo durante un curso escolar completo. Los alumnos y los educadores han valorado muy positivamente la plataforma y las actividades que se pueden realizar con ella. Se ha podido ver como los métodos de aprendizaje participativos, colaborativos, activos y centrados en el alumno, combinados con tecnologías novedosas y amigables, tienen un gran impacto en la educación, y proporcionan una alternativa válida al aprendizaje tradicional.

- Participación en proyectos Erasmus+.

Parte de las trabajos realizados en esta tesis han dado lugar a la realización del proyecto Erasmus + *“Wearable Methodology”* K201-025397. En este proyecto han participado tres colegios de educación primaria de tres países, St. Kliment Ohridski School (Chirpan, Bulgaria), Zoranić Croatia Petar Nin School (Zadar, Croacia) y CEIP Anton Diaz (El Bonillo,España). El proyecto ha consistido en la implantación real de la plataforma *IoT y Wearable* en estos tres colegios. Durante la realización de este proyecto educadores de los tres colegios participaron en el diseño final de la plataforma así como en la creación de contenidos educativos. Más de 300 alumnos y 11 profesores de los tres colegios han participado en la evaluación y validación tanto de la plataforma como del dispositivo *wearable*. La evaluación final de proyecto por parte de la autoridades europeas fue muy positiva destacándolo como proyecto con buenas practicas.

Como consecuencia de la participación proyecto Erasmus + *"Wearable Methodology"*, ha surgido la participación en el proyecto Erasmus + *"Code Is Loading"* KA201-058963. Este proyecto se centra en mejorar las habilidades de programación en alumnos de enseñanza secundaria de cinco paises, Ali Osman Sönmez Vocational and Technical High School (Bursa, Turquia), Lyceum of Human Sciences E. Gianturco (Potenza, Italia), Bálint Márton Általános Iskola és Középiskola (Törökbálint, Hungria), Centrum Edukacyjne EST (Wadowice, Polonia) y Agrupamento De Escolas Domingos Sequeira (Leiria, Portugal).

- Colaboraciones.

En colaboración con la Facultad de Educación de Albacete, se han desarrollado seis Trabajos Fin de Grado y un Trabajo Fin de Master, utilizando la plataforma *IoT y Wearable* como base tecnológica. Estos trabajos se han centrado en la utilización de la plataforma para intensificar materias con alumnos en general y con alumnos con necesidades espaciales, obteniendo resultados muy positivos.

Con el trabajo desarrollado en las publicaciones que conforman el compendio, se ha completado el objetivo principal y los objetivos específicos previstos en el la sección 1.2, también se han dado respuesta a todas las cuestiones de investigación planteadas.

## 4.2 Perspectivas de Futuro

Como perspectivas de futuro para esta investigación se plantea seguir explorando las capacidades del la plataforma *IoT y Wearable* incorporando nuevas características y ampliando sus capacidades en el ámbito del *Learning Analytics*. De las lecciones aprendidas durante la realización de esta investigación surgen de forma inmediata las siguientes investigaciones futuras:

- Ampliar el estudio con un mayor número de estudiantes, niveles y actividades, con lo que se podrá extraer una taxonomía más extensa que permitirá caracterizar de forma más amplia el comportamiento de los alumnos.

- Incorporar al dispositivo *wearable* más sensores, con esto se podría ampliar el rango de actividades en las que se puede utilizar, como por ejemplo incorporación de sensores de actividad, GPS, etc. Con esto se obtendría información sobre los alumnos y su comportamiento, al mismo tiempo que se ampliarían los campos de aplicación de la plataforma.

- Incluir en la plataforma herramientas del profesor, para mejorar como se muestran en tiempo real los patrones de comportamiento y la motivación de los alumnos mientras utilizan la plataforma. Así el sistema ayudará in situ a los educadores a evaluar la motivación de los alumnos y a tomar decisiones para implicar a los alumnos en las actividades. Los educadores pueden tener una retroalimentación rápida, de modo que, durante las actividades, son conscientes de qué alumnos presentan problemas de desvinculación. Si este diagnóstico se realiza a tiempo, podrán reformular la estrategia de enseñanza con el objetivo de fomentar la implicación de esos alumnos concretos, pudiendo así atajar el problema del abandono escolar.

- Basados en resultados preliminares, extender el uso de la plataforma a otros campos de aplicación como la utilización como en actividades de formación dentro de la Industria 4.0, así como en terapias la rehabilitación cognitiva, prevención de la enfermedad de Alzheimer y la demencia, entre otras.

## 4.3 Conclusions

This thesis has focused on studying how the use of ICT, specifically IoT and Wearable technologies, can contribute to reduce early school dropout levels through improving students' motivation levels. An extensive literature review has been conducted on how IoT and Wearable technologies can increase student motivation. Evaluations have confirmed that the use of these technologies generates intrinsic motivation in learners. In addition, these evaluations allow the collection of a large amount of data on how students perform the activities. These data, processed under the approach of Learning Analytics methodologies, provide educators with information about the level of motivation of the students. With this information, educators can take measures to avoid the demotivation of students in school and thus prevent school dropout.

- Hardware and software design of the educational platform.

With the participation of primary and secondary education teachers, a study has been carried out on how to introduce IoT and Wearable technologies in educational activities. With this information, an educational platform has been designed based on a tangible human interface, with an intuitive interaction mechanism through wearables devices. This platform is an interactive and collaborative system designed to enhance motivation and learning. The design has been validated through multiple evaluations with students of all ages and levels in which they have carried out different activities related to foreign languages, geography, mathematics, spelling, etc. With the results of all the evaluations and feedback from end users, the platform has been improved and new features have been incorporated. It has been developed using technologies already available, such as NFC, WiFi, WebSocket, JavaScript and cloud-based web applications. A new platform-specific wearable device has also been developed to simplify user interactions. It is based on an SoC microcontroller, integrates an NFC reader, has WiFi connectivity, and a visual and haptic interface. The development of the platform and the wearable device has been carried out in a continuous development cycle and has shown, as one of its most outstanding features, its capacity for improvement and expansion.

- Design of the data capture and analysis system.

Integrated in the platform, a system has been developed to capture the data generated by the students with their interactions while performing the activities. With this data and applying the Learning Analytics approach, it has been possible to extract a taxonomy of behavioral patterns related to student motivation. With this taxonomy, the interaction data and applying Machine Learning techniques, a model has been created that allows in real time to inform educators about the level of motivation of the students during the activities. To obtain the taxonomy and the model, about 400 different activities have been carried out by 18 students of the Diocesan School of Albacete, in a long-term study during a full school year. The students and educators have valued the platform and the activities that can be carried out with it very positively. It has been possible to see how participatory, collaborative, active and student-centered learning methods, combined with new and friendly technologies, have a great impact on education, and provide a valid alternative to traditional learning.

- Participation in Erasmus+ projects.

Part of the work carried out in this thesis has led to the realization of the Erasmus + project *"Wearable Methodology"* K201-025397. Three primary schools from three countries participated in this project, St. Kliment Ohridski School (Chirpan, Bulgaria), Zoranić Croatia Petar Nin School (Zadar, Croatia) and CEIP Anton Diaz (El Bonillo, Spain). The project consisted in the actual implementation of the IoT and Wearable platform in these three schools. During the realization of this project, educators from the three schools participated in the final design of the platform as well as in the creation of educational content. More than 300 students and 11 teachers from the three schools participated in the evaluation and validation of both the platform and the wearable device. The final evaluation of the project by the European authorities was very positive, highlighting it as a best practice project.

As a consequence of the participation in the Erasmus + *"Wearable Methodology"* project, the participation in the Erasmus + *"Code Is Loading"* KA201-058963 project arose. This project focuses on improving programming skills in high school students from five countries, Ali Osman Sönmez Vocational and Technical High School (Bursa, Turkey), Lyceum of Human Sciences E. Gianturco (Potenza, Italy), Bálint Márton Általános Iskola és Középiskola (Törökbálint, Hungary), Centrum Edukacyjne EST (Wadowice, Poland) and Agrupamento De Escolas Domingos Sequeira (Leiria, Portugal). Among other objectives, this project focused on improving students' motivation when learning to program.

- Collaborations.

In collaboration with the Faculty of Education of Albacete, six final degree projects and one final master project have been developed, using the IoT and Wearable platform as a technological base. These works have focused on the use of the platform to intensify subjects with students in general and with students with spatial needs, obtaining very positive results.

With the work developed in the publications that make up the compendium, the main objective and the specific objectives foreseen in section 1.2 have been completed, and all the research questions raised have also been answered.

## 4.4 Future Outlook

As future outlook for this research, it is proposed to continue exploring the capabilities of the IoT and Wearable platform by incorporating new features and expanding its capabilities in the field of Learning Analytics. From the lessons learned during the development of this research, the following future research immediately emerges:

- Expand the study with a larger number of students, levels and activities, which will allow us to extract a more extensive taxonomy that will allow us to characterize more broadly the behavior of the students.
- Incorporate more sensors to the wearable device, with this it would be possible to expand the range of activities in which it can be used, such as incorporating activity tracking sensors, GPS, etc. This would provide information about the students and their behavior, while expanding the platform's fields of application.
- Include teacher tools in the platform, to improve how the behavior patterns and motivation of learners are displayed in real time while using the platform. Thus the system will help on-site educators to assess learner motivation and make decisions to engage learners in activities. Educators can have quick feedback, so that, during activities, they are aware of which learners present disengagement problems. If this diagnosis is made in time, they can reformulate the teaching strategy with the aim of encouraging the involvement of those particular students, thus being able to tackle the dropout problem.
- Based on preliminary results, extend the use of the platform to other fields of application such as the use in training activities within Industry 4.0, as well as in cognitive rehabilitation therapies, prevention of Alzheimer's disease and dementia, among others.

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*Por que aprendieron, aprendemos; porque aprendemos, aprenderán.*