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USING PHYSICAL COMPUTING TO CROWDSOURCE ENVIRONMENTAL DATA VIA THE INTERNET OF THINGS

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ABSTRACT
Physical computing involves the use of small electronic devices such as single-board computers as learning tools. These devices can be used across many mobile contexts, including environmental monitoring through external sensors. This paper explores a learning design for an activity that uses the micro:bit, a single board computer designed for educational use, to connect a network of sensors and data receivers to create an Internet of Things architecture for environmental monitoring. To provide an authentic context for the learning, the learning design involves the use of environmental sensors to monitor the state of the students' learning environments. The learning activity includes the gathering of data by deploying sensors across different locations and the crowdsourcing of that data with other learners via the Web to support data analysis across different contexts. From a pedagogical perspective, these mobile learning activities provide an opportunity for situated cognition using tools, collaboration, and a cognitive apprenticeship process, which provides the sequencing of the learning design from situated activity to generality. The TPACK framework is used to integrate the technology component into the pedagogical scaffolding.

Keywords: physical computing; micro:bit; Internet of Things; situated cognition; TPACK; crowdsourcing.

1. INTRODUCTION

Physical computing involves the use of portable single-board computers such as the micro:bit, Arduino and Raspberry Pi as learning tools. A single-board computer (SBC) is a complete computer system built on a single, small circuit board, containing the essential components of a computer - processor, memory, storage, and input/output channels. Being small and light, they are highly portable and can be embedded in larger systems. Depending on how they are applied, they can be useful components in mobile learning scenarios. This is a technical/theoretical paper that describes a learning design for a physical computing environment. It outlines the intended learning outcomes and how they are met in a learning activity that explores a process of crowdsourcing environmental data gathered from the students' learning environments using small Internet of Things (IoT) networks. It describes the technology required and how it can be used at each stage of the learning design. This includes micro:bits and external sensors, example code for each step of the process, and a dedicated web app that has been created to enable students to crowdsource and visualise data. Examples of the technology in use are included in this article to illustrate some of the activities in the learning design.

The article is structured as follows. The remainder of this introduction provides more detail about single-board computers, micro:bits, and using IoT and crowdsourcing in a learning environment. The next section describes the learning design using the TPACK framework, using situated cognition as the pedagogical component. The three main stages of the learning process are then illustrated using the process of cognitive apprenticeship to scaffold the learning. This is followed by some conclusions and a discussion of limitations and future work.

1.1 Single Board Computers

Single Board Computers (SBCs) can be coded in various ways to be usable across many mobile contexts. For example, they can be used as stand-alone devices to create simple digital tools such as step counters or compasses. In addition, they can be connected either physically or wirelessly to other devices, for example, they can be used as remote Bluetooth controllers or participate in publish-subscribe radio networks and be connected to a range of different types of sensors. Gathering atmospheric data that can be crowdsourced for analysis is one example of the value of such sensors (Budde, 2021). The combination of communication channels and sensors provides students with many opportunities for scientific discovery and related mathematical skills. For example, SBCs have proved effective in a range of project-based learning activities in the secondary classroom (Steinmeyer, 2015).

1.2 The micro:bit

The micro:bit is a popular SBC, being both affordable and specifically designed for educational use. It provides an LED display, input buttons, radio and Bluetooth connections, USB and battery sockets, and some onboard sensors: light, temperature, direction (compass), acceleration and, from version 2, touch, and sound. The onboard sensors are a key component of the micro:bit's design. The intention was to enable learners to engage creatively with the device and explore a world where sensor-based devices are ubiquitous (Knowles et al., 2018). In addition, a range of external sensors can be connected to a micro:bit using various combinations of external connections (pins) on the edge connector of the board. The micro:bit is prevalent in many classrooms, particularly in the UK, where a million middle school students were given one in 2016 (Ball et al., 2016). A similar exercise took place in 2023 when class sets of 30 version 2 micro:bits were offered to all UK primary schools (BBC, n.d.).

1.3 Learning with the Internet of Things

Integrating the Internet of Things (IoT) into education is a topic that has been previously explored from a range of perspectives. Many examples focus on the technical aspects of IoT networks, but they have also been used across other subject areas, including science, languages, physical education, and business (Kassab et al., 2019). The benefits of learning in an IoT environment have been claimed to include raising awareness about sustainability and ethics (Zeinab et al., 2022), but perhaps the broadest motivation is to expose students to ubiquitous devices that can be of benefit to everyone (Richards &

Woodthorpe, 2009).

micro: bits were designed from the beginning as a means of learning about the Internet of Things (IoT) but since they do not have on-board Internet connections, other components are needed to enable them to become true IoT components, for example by connecting Wi-Fi expansion boards or linking them with internet-enabled devices such as Raspberry Pis or laptop/desktop computers.

1.4 Mobile Crowdsourcing

Crowdsourcing has previously been used for learning about IoT (Hussein et al., 2019), but the learning design in this article is focused on learning through crowdsourcing using IoT as a platform. Further, this activity is based on mobile crowdsourcing. The main characteristics of mobile crowdsourcing are the mobility of devices and their carriers, collaboration through distribution of tasks to achieve a global objective, and human capacity, where individuals are data consumers and producers, and their capabilities enhance the performance of the overall system (Kong et al., 2019). The mobile aspect is important in this learning design because of the element of physical computing in the intended learning experience.

2. THE LEARNING DESIGN AND TPACK

The introduction to this article has described the single board computer as a device suitable for learning, the micro:bit as an educational SBC, and the Internet of Things as a platform to support the mobile crowdsourcing of data gathered from sensors. The learning activity design outlined in this section integrates micro:bits, the IoT, sensor data and crowdsourcing in ways that enhance student learning beyond just the technical content of electronics and coding. At the end of this learning activity, the learner should be able to:

1. Explain the impact of environmental factors on learning spaces,
2. Implement a system of mobile sensors that can gather data from the environment,
3. Demonstrate an understanding of the meaning of data gathered and the parameters of data gathering,
4. Analyse environmental data to draw conclusions about the impacts and mitigations of environmental factors.

To ensure that the activity design has an appropriate pedagogy, the concept of cognitive apprenticeship, from situated cognition theory, has been used to scaffold the learning process (Brown et al., 1989), while the TPACK framework has been applied to integrate the technology with the content and pedagogy (Koehler et al., 2012). This is described in detail in the remainder of this section. This learning design has been developed from a previous series of workshops that prototyped the first two stages of the activity and established some design principles (Parsons & MacCallum, 2022).

2.1 Applying TPACK

Although there are many ways of applying a framework such as TPACK (Technological Pedagogical

Content Knowledge), assessing its impact on practice relies on observation of performance and assessment (Koehler et al., 2012). In addition, the complexity of TPACK (with its seven knowledge constructs) and its emphasis on the technology part of the Pedagogy / Content / Technology triad, means that applying it effectively of necessity means focusing on the PCK (Pedagogy Content Knowledge) supported by the technology (Brantley-Dias & Ertmer, 2014). This is challenging in a situation where technology is a significant component of the learning environment. Previous research into teacher practice when using micro:bits for learning suggests that demonstrations, collaborative work and guided discovery are widely seen as relevant approaches to learning through physical computing. However, teachers are often not able to fully meet their intentions when working with these devices and do not always deliver learning activities that take full advantage of tactile feedback experiences (Kalelioglu & Sentance, 2020). Learning with single-board computers, such as the micro:bit, often focuses on the technology, but lacks a coherent educational approach (Ariza & Baez, 2022).

The learning design outlined in this paper attempts to address these shortcomings by providing a more structured theoretical basis for the learning process. The use of technology is driven by content that is authentic within the students' own learning environment, and the pedagogy is based on cognitive apprenticeship, where the role of the technology is to represent generalised concepts of the learning content and the learning activities with that technology follow the apprenticeship pathway.

2.2 The Content Knowledge in the Learning Design

In the learning design, the content is based on issues related to the physical classroom environment, which have been brought to the fore in recent discussions about the safety of students at school during the COVID-19 pandemic. For example, ventilation levels can be measured by monitoring CO2 concentrations, which can also have a direct impact on student well-being, as do a range of other environmental factors. This learning design aims to give students an opportunity to learn about their own environments while gaining a deeper understanding of the importance of environmental factors for their own well-being.

Many previous studies have explored the impact of different environmental factors in the classroom. These have included lighting, temperature, and humidity (Runathong et al., 2017; Lakshaga Jyothi & Shanmugasundaram, 2021). Several studies have monitored levels of CO2 in classrooms and their potential impacts (Shendell et al., 2004; Gaihre et al., 2014). To successfully use environmental sensors as part of the learning process students must gain a proper understanding of what the sensor data means and how it is used. They need to be able to understand how code and components work together as a feedback system to produce the desired outcomes (Cederqvist, 2022). In addition to this theoretical and technical content, students should be able to gather their own data, share it, analyse it, consider its implications and mitigations, and thereby contribute to their own content knowledge.

2.3 The Pedagogical Knowledge in the Learning Design

Cognitive apprenticeship, as embodied in the theory of situated cognition, structures the progress of learners from embedded activities to general principles (Brown et al., 1989). This sequence begins with apprenticeship and coaching, where educators provide modelling and scaffolding for students to get started in authentic activities. This is followed by a more autonomous phase of collaborative learning, with learners experiencing multiple roles and practices, which leads to them articulating and reflecting on strategies. From this situated understanding, the students' conceptual knowledge can be generalised and further developed (Figure 1).

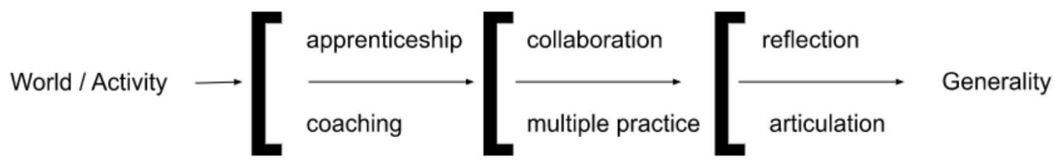

Figure 1. The process of cognitive apprenticeship (adapted from Brown et al., 1989)

These three apprenticeship stages in the pedagogy map to the development steps in content and technological knowledge. First, students gain an understanding of the impacts of various environmental factors in their own learning spaces, and technical content knowledge about how to use micro:bits and sensors to gather environmental data. Then, collaboratively, they gain knowledge from multiple perspectives by exploring their repertoire of data-gathering tools and gain a deeper understanding of this data through reflection. Finally, through a crowdsourcing process they can reflect on multiple sources of data and articulate possible solutions to environmental problems.

2.4 The Technological Knowledge in the Learning Design

To access the content knowledge in the learning process, students need to develop technical knowledge about the hardware and software that is used during the learning. In this case, the hardware is the micro:bit and a range of external sensors, and the software comprises the Microsoft MakeCode Editor and a PHP-based web application. In summary, during the learning activity, students will develop technological knowledge of coding the micro:bit, using its internal sensors, connecting external sensors and gathering data from them, sending data via radio between micro:bits, sending serial data from a micro:bit to the MakeCode editor via USB, monitoring and saving sensor data, uploading it to a server and accessing multiple crowdsourced files and visualisations using a web app.

3. THE STEPS IN THE LEARNING ACTIVITY

The learning activity is divided into three steps, each of which is based on one stage of the cognitive apprenticeship. Each step relates to a pair of features of the apprenticeship process. In this section, the content, pedagogy, and technology that relate to these steps are described.

3.1 Step 1

Content: Using sensors to measure the environment. Foundational content knowledge about environmental factors and their impacts is provided, along with applied knowledge of using the hardware and software.

Pedagogy: The first phase of cognitive apprenticeship is based on coaching, where in situ modelling and scaffolding are provided for students to get started in an authentic activity, and apprenticeship, where learning is embedded in authentic activities that make deliberate use of the social and physical context. These are embodied in this step of the learning activity as follows:

- Coaching - scaffolded instructions and explanations are given, and the technology is demonstrated.
- Apprenticeship - Students code their own devices and use them to explore their environment, making links between data and context.

***Technology*:** micro:bits and coding in the MakeCode editor.

Figure 2 shows the technology components used for this step in the cognitive apprenticeship learning process. While connected to the MakeCode editor on a computer, micro:bits are coded by the students to receive data directly from their own internal sensors. They can then experience mobile data gathering by disconnecting the micro:bits and using them in different parts of the environment to measure factors such as sound, light, and temperature.

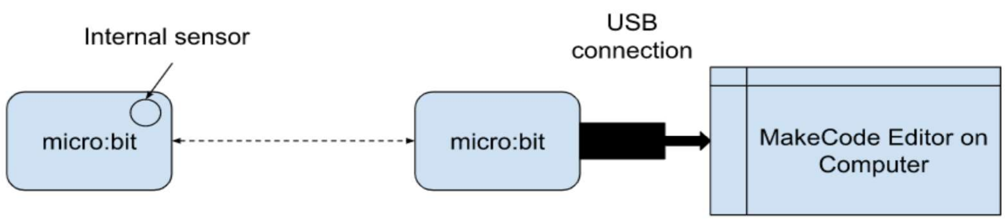

Figure 2. The technology engaged in the first learning step - micro:bits and their internal sensors

3.2 Step 2

Content: Gathering and visualising data from environmental sensors. Students learn about different types of environmental measures and their meanings. They extend their technical knowledge and skills, learning how to remotely capture a stream of sensor data, while critically thinking about solving problems collaboratively.

Pedagogy: The second phase of cognitive apprenticeship is based on collaboration and multiple practice. When collaborating, students engage in collective problem-solving, understanding the many different roles needed for a task, confronting ineffective strategies and misconceptions, and gaining collaborative work skills. In multiple practice, students can compare multiple performances, leading to mastery learning. These are embodied in this step of the learning activity as follows:

- Collaboration: Students are given group challenges with additional technical layers, needing to problem-solve independently
- Multiple practice - students revisit their devices and code and use them in enhanced ways, further developing their skills.

***Technology**:* micro:bits and external sensors forming a small IoT network, data gathering and visualisation in the MakeCode editor, and exporting data to files for analysis. Figure 3 shows the technology components used for this second step in the cognitive apprenticeship learning process.

A micro:bit network is set up where multiple micro:bits receive sensor data (either directly through their own sensors or via serial input from external sensors), and then broadcast that data over a radio channel to a micro:bit that is connected to a computer via USB. Data sent from the receiving micro:bit to the computer can be captured locally from the MakeCode editor either as a CSV file or a text file.

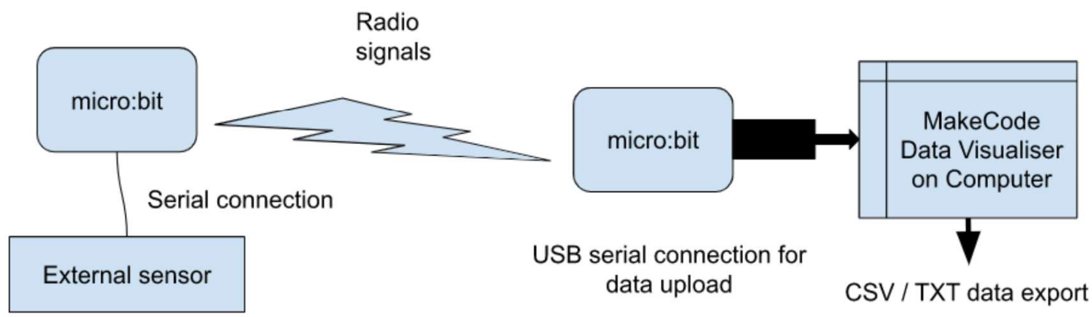

Figure 3. The technology engaged in the second learning step - an IoT architecture of micro:bits with external sensors

The test environment used for developing this step included a range of external sensors, including light, sound, temperature, pressure, humidity, and CO2. For most of these measures, there is more than one sensor available so students can compare values for consistency. The external sensor boards used in the test environment are shown in Table 1. Each sensor board can measure more than one environmental variable. Several boards have MakeCode extensions that make coding easier for learners to program them for use in their own environments. It is worth noting that sensors for sound and light return values that are on arbitrary scales and are therefore only relative, for example, sound sensors are just noise sensors that can, for example, respond to a clap. In contrast, sensors for CO2, temperature, humidity, and pressure all return values that relate to standard measures and can therefore be compared across different devices.

Table 1. External sensors used with the micro:bit

Sensor Board	Sensors	MakeCode Extension	Notes
MonkMakes COZIR sensor	C02, temperature, humidity	Yes	Has its own power supply
MonkMakes air quality sensor	C02, temperature	No	The temperature sensor is used to support the C02 sensor but can also be used separately
MonkMakes sensor board	Temperature, light, sound	Yes	Light and sound levels are measured between 0 and 100
Pimoroni enviro:bit	Temperature, pressure, humidity light (including red, green, and blue levels), sound	Yes	The micro:bit plugs directly into the board. Light level is measured between 0 and 255 and sound level between 0 and +-344

Figure 4 shows an example of micro:bit sensor data being gathered in the MakeCode editor. In this case, a temperature sensor is being used to gather data, which is sent as a serial data stream over a USB connection to the editor. As can be seen in Figure 4, the editor displays the data as text and as a visualisation. However, these representations are ephemeral, so to be able to make further use of the data it needs to be saved to a file so it can be processed elsewhere. The buttons on the right side of the screen allow the data to be downloaded either as a text or CSV file (a comma-separated file that can be read by spreadsheet software such as Microsoft Excel and Google Sheets). In Step 3 of the learning design, students take CSV files created in this way and share them in a web application designed for this activity.

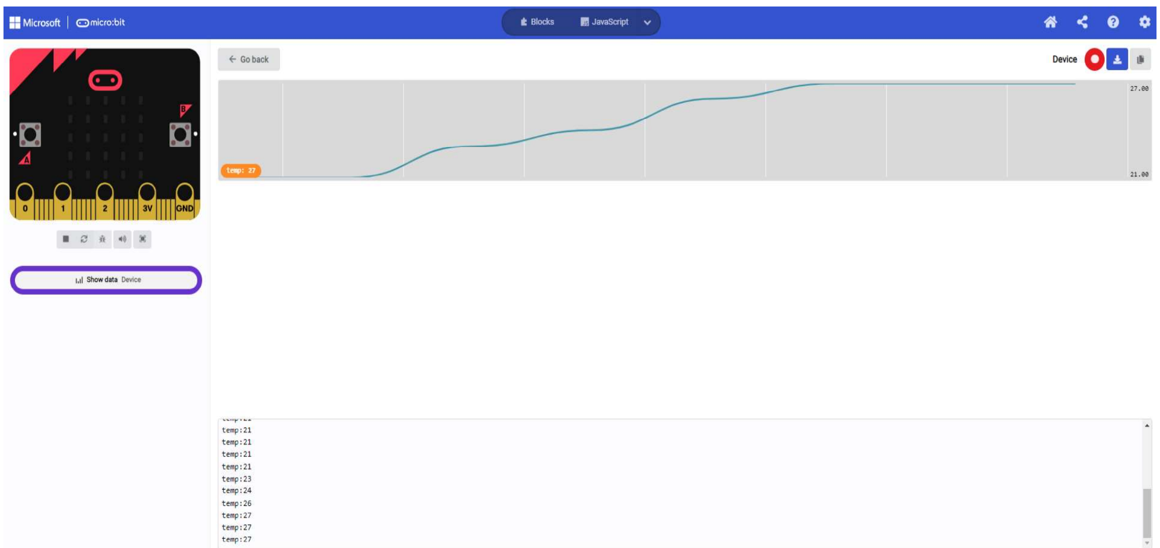

Figure 4. micro:bit sensor data being gathered in the MakeCode editor

3.3 Step 3

Content: Mobile crowdsourcing and analysing data from environmental sensors. Students learn about how to best collect data and apply metadata, share, and analyse large data sets, interpret visualisations, and potentially draw conclusions about how to manage the classroom environment.

Pedagogy: The third phase of cognitive apprenticeship is based on articulation, where students articulate strategies so they can be discussed and reflected upon, and reflection, where students reflect upon, evaluate, and validate the collaborative activities and the performances and roles within them. These are embodied in this step of the learning activity as follows:

- Articulation: Students collectively articulate their strategies for data gathering, sharing, and analysis.
- Reflection: Students reflect upon what happened during their collaborative activities and the outcomes. They consider future actions resulting from their learning.

Technology: web-based crowdsourcing and collaborative data analysis.

Figure 5 shows the technology components used for this final step in the cognitive apprenticeship learning process. Data captured in the previous step can be shared as CSV files using a dedicated web app. This app supports the crowdsourcing of data from multiple locations. Students can then access this data to visualise it or download it to perform their own analyses.

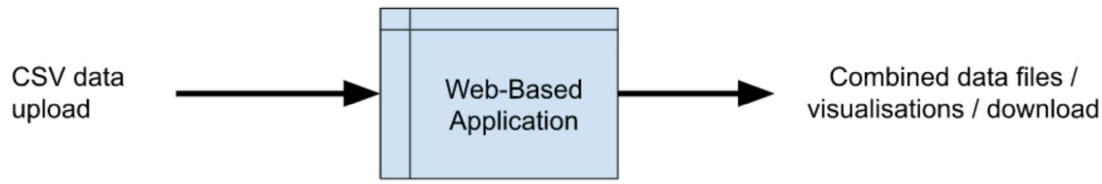

Figure 5. The technology engaged in the third learning step - crowdsourcing data.

Figure 6 shows the upload page of the Web application. Students can upload their CSV files to the server and add some metadata about where and when their measures were taken, and what environmental variable the measures relate to.

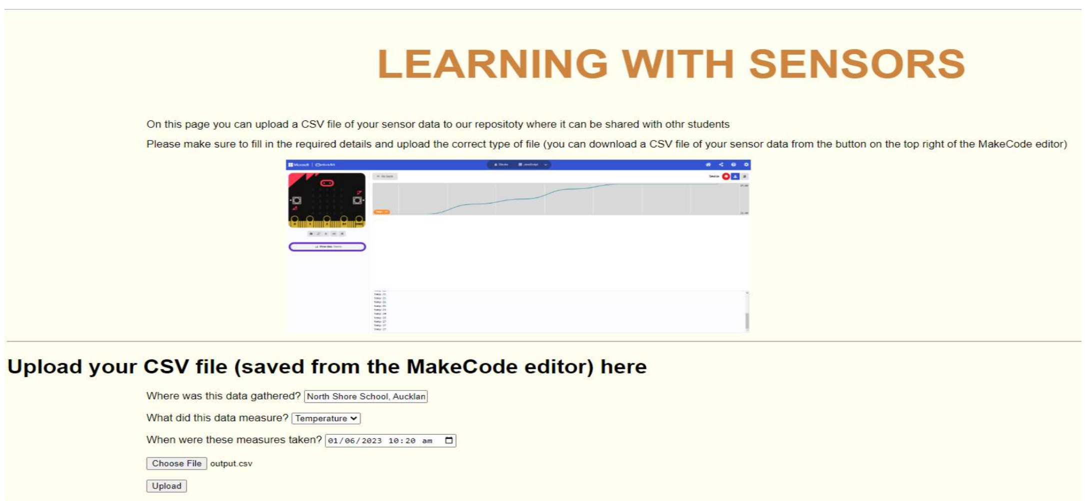

Figure 5. The upload page of the web application where students can share their data.

Once files have been uploaded, they can be viewed, downloaded, or visualised by anyone as a crowdsourced data set. Figure 6 shows the page that lists the available data files. Clicking on a filename will download a file and clicking on 'View Graph' will generate a line graph from that file's data.

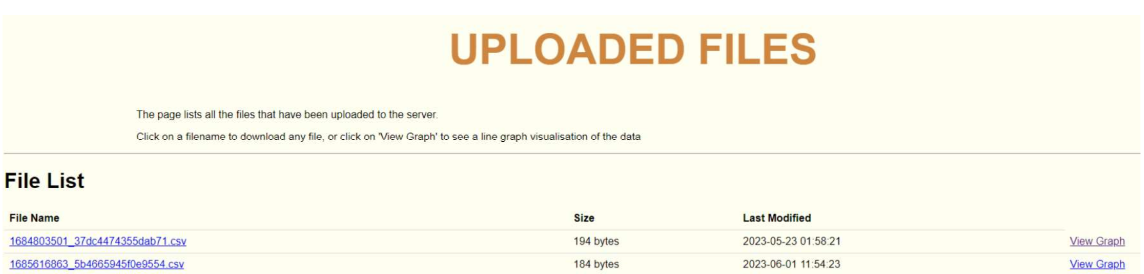

Figure 6. The file list page where students can download or visualise files.

As an example of the type of web-based visualisation possible in the activity, Figure 7 shows a short temperature trace gathered from an external micro:bit sensor over a period of 90 seconds, with measures taken at 5-second intervals, displayed using the 'View Graph' option on the web app page that aggregates multiple data sets.

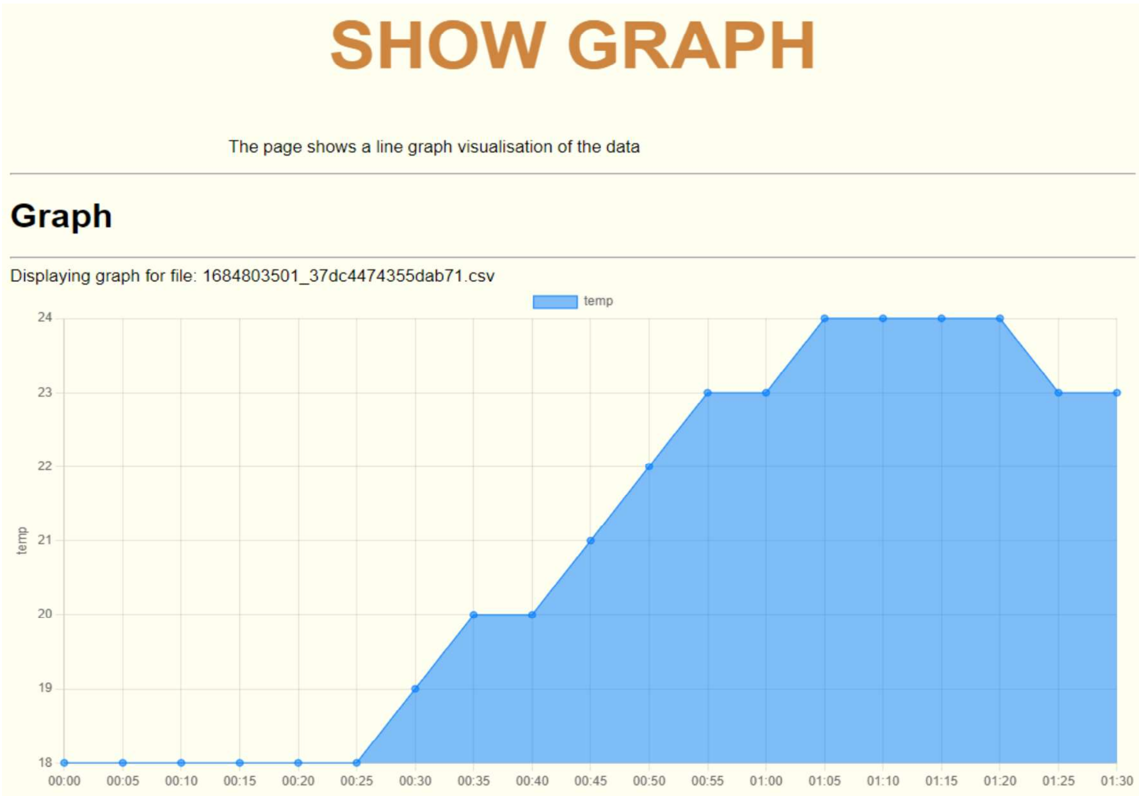

Figure 7. An example visualisation of micro:bit sensor data uploaded to a web app.

4. SUMMARY AND CONCLUSIONS

This article has presented a learning activity design based on students exploring the potential of using physical computing in the classroom, with a particular focus on investigating environmental factors that can be monitored by sensors connected to single-board computers (the micro:bit in this case). The design of the activity was structured within the TPACK framework and grounded in the process of cognitive apprenticeship. Taking the process of cognitive apprenticeship as outlined in Figure 1 and overlaying the activities from the three steps outlined in the previous section, the mapping of the learning design to the underlying cognitive apprenticeship process is shown in Figure 8.

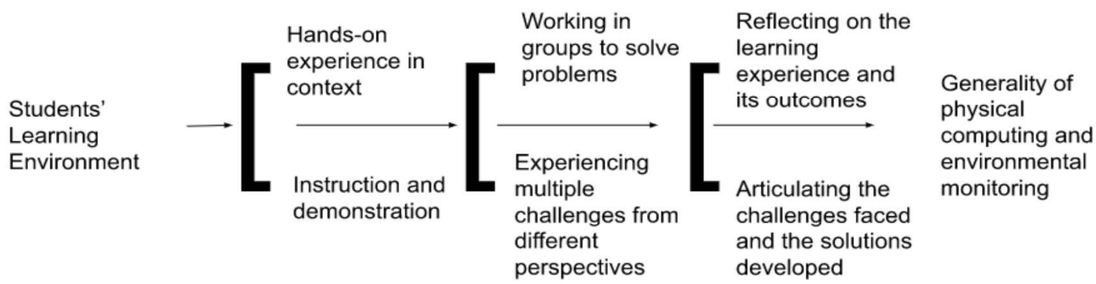

Figure 8. The process of cognitive apprenticeship as embodied in the learning design

This learning activity maps closely to Kong et al's (2019) definition of mobile crowdsourcing because of the mobility of the sensors, the collaborative component of the pedagogy, and the learning tasks of producing and consuming data. Mobile crowdsourcing can have a range of different characteristics (Kong et al., 2019) that can be identified in the final step of the learning activity. It is participatory (data and metadata is submitted consciously), both audience-driven (participants are at the centre) and location-driven (focusing on a particular place), involves both sensing and analytical tasks, and contributions are homogeneous (combined and equally weighted).

Learning activities such as the one described in this paper can provide students with an opportunity to use small mobile, electronic devices for real-world learning with opportunities to develop skills in digital technologies, data analysis, and real-world problem-solving. By taking account of the need to balance technology, pedagogy, and content within the TPACK framework, and applying a suitable pedagogy based on situated cognition, the design seeks to ensure that the technology content does not dominate the learning.

4.1 Limitations and Future Work

The work reported in this article is only design-based and has not been empirically validated. However, it was informed by previous research in a similar area and builds on the outcomes from that work. It is therefore the next step in an ongoing effort to explore the potential of physical computing in mobile learning. As a technical study that can inform ways in which to design physical computing experiences in a specific domain of knowledge, it provides some insights into designing the learner experience that will be valuable going forward. The web application that has been developed to support the activity is also rudimentary at this stage and would need more development to be suitable for deployment on a public server for use by large numbers of students but is sufficient for small workshop use.

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