Developing and Using Disruptive Technologies in Agricultural Education

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This paper looks at different technologies that are being used currently in agricultural education at the University of Queensland (UQ), Australia through the lens of 'disruption' as a positive force. The paper describes tools and systems that have been developed, tested and implemented to engage students and provide an interesting, educative interactive experience. These tools include Internet of Things (IoT) multisensory mesh networks and associated data dashboard developments for biophysical monitoring, drone technology design and build for agricultural management, and augmented reality simulations as blended learning experiences. These tools have all been used in teaching from 2018-2020.

Keywords: internet of things, drones, data dashboards, augmented reality

INTRODUCTION

It is difficult to get young people whether they come from a rural background or not, into agriculture and related areas, because the sector is perceived as labour intensive, non-academic and lowly paid. Actually, this is far from the truth, but the perception is there among young people and their parents (Bryceson, 2006; Nat West, 2019), and it is not only frustrating the agrifood industry generally, but also educators in the sector. A potential solution or at least part of a potential solution to both of these problems in the agrifood sector is to use digital technologies as means of innovating legacy systems. This is then followed by using those same digital technologies as a 'disruptive agent' to change the way agricultural education is undertaken in order to increase student engagement - both with education and with the agrifood sector in general (Bryceson et al., 2016a; 2016b; 2017).

Technology as a 'Disruptive' Agent

A disruptive innovation or technology is one that can 'disrupt' or 'overturn' traditional business methods and practices and which in the long term, can leads to the creation of new 'ground-breaking' products (Christensen & Overdorf, 2000); (Millar, Lockett & Ladd, 2018).

Over the last decade, disruptive technologies in the form of the Internet, mobile computing (including social media for marketing purposes), Internet of Things (IoT) technologies (to collect and transmit real time data), the use of cloud computing (to facilitate the analysis of data generated), 'Big Data' and Robotics (to make use of the data), have been identified as having impacted the agrifood industry in an unprecedented way to create and capture value across the whole chain (Bryceson, 2006; Bourlakis et al., 2011; Lehmann et al., 2012; Hall, 2016; Bryceson & Yaseen, 2018; Bryceson, 2019).

ICT technology as a disruptive agent in education, particularly in higher education, has been much discussed starting in the late 1990s with the advent of the internet and then onwards with the number of articles discussing different aspects of 'disruptive' technologies increasing significantly. For example Archer et al. in 1999 identified that the internet was likely to be a disruptive technology in higher education generally with learning materials delivered "online" via the internet; Sharples (2003) talked about using mobile phones as tools for learning; Garrison & Kannuka (2004) discussed the notion of blended learning as "[combining] *text-based asynchronous Internet technology with face-to-face learning*"; while Bryceson (2007) discussed linking models of knowledge acquisition, Elearning and online immersive worlds to create an innovative online learning environment to be used both for higher education and for lifelong learning strategies. Such ICT technologies although prevalent at this time were not necessarily the ubiquitous force in the world that they are now and Flavin (2012), concluded that only a narrow range of technologies were really being used to support education such as Google or Wikipedia but that these technologies did indeed 'disrupt' the traditional means of supporting learning.

Fast forward 5 years and by 2017, the world of disruptive technologies used in education had developed further with Sagenmüller (2017) predicting Virtual Reality (VR) e.g. VRChat; Collaborative platforms such as Google docs, Augmented Reality e.g. Microsoft Hololens, and Artificial Intelligence (AI) as the next most promising innovations that will "revolutionise" learning.

The work reported in this paper looks at how it is possible to create engagement and more realistic learning opportunities in agriculture for young people using a combination of 'disruptive' educational technologies – Internet of Things and Data Dashboards, Drone design and build and 3D Holographic Augmented Reality (AR) assets - along with a tried and tested educational approach of "Active" Problem Based Learning (PBL) (Schmidt, 1983; Wood, 2003; Prince, 2004).

Disruptive Agricultural Education Tools

Internet of Things and Data Dashboards

The 'Internet of Things' (IoT) is defined as: "A network of physical objects that contain embedded technology to communicate, sense &/or interact with their internal states or the external environment and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction" (Gartner, 2016). With the growing popularity of the Internet of Things (IoT) technology, (which includes both smart wireless network technology and sensor nodes), there has been extensive research on the use of wireless sensor networks or IoT in agricultural research studies, ranging from on farm through to market and into agricultural education. (Vellidis et al., 2008; Kim et al., 2008; Bryceson et al., 2016a; Stočes et al., 2016; and Gunesekra et al., 2018).

The UQGatton IoT network is described in Bryceson et al., (2016a) - it's development commenced in December 2014 and was aimed at creating an IoT multisensory mesh network encompassing everywhere on University's rural 1000ha campus at UQGatton, 80kms south of Brisbane in SE Queensland, covered by Wi-Fi and/or LORA radio technologies. The network was set up for agricultural and environmental biophysical data collection in the managed landscape, for research and educational purposes.

A significant amount of time went into the design of the IoT mesh network and in choosing the technologies involved. The main requirements were that there was a large area to cover so a network typology was needed that was flexible, self-configuring, self-healing (ie fault tolerant) and able to relay data over long distances, we chose a mesh multi-hop network (Zawawi et al., 2012), [Figure 1]. We also needed a wide choice of sensors enabling many problem scenarios to be developed and the network needed to be robust and have low set-up and maintenance needs and costs [Figure 2]. Note images of models shown in Figure 2 are from the Libelium webpage - http://www.libelium.com/products/plug-sense/models/ and a list of the Libelium sensors being used at UQGatton can be seen at: http://www.libelium.com/products/plug-sense/models/

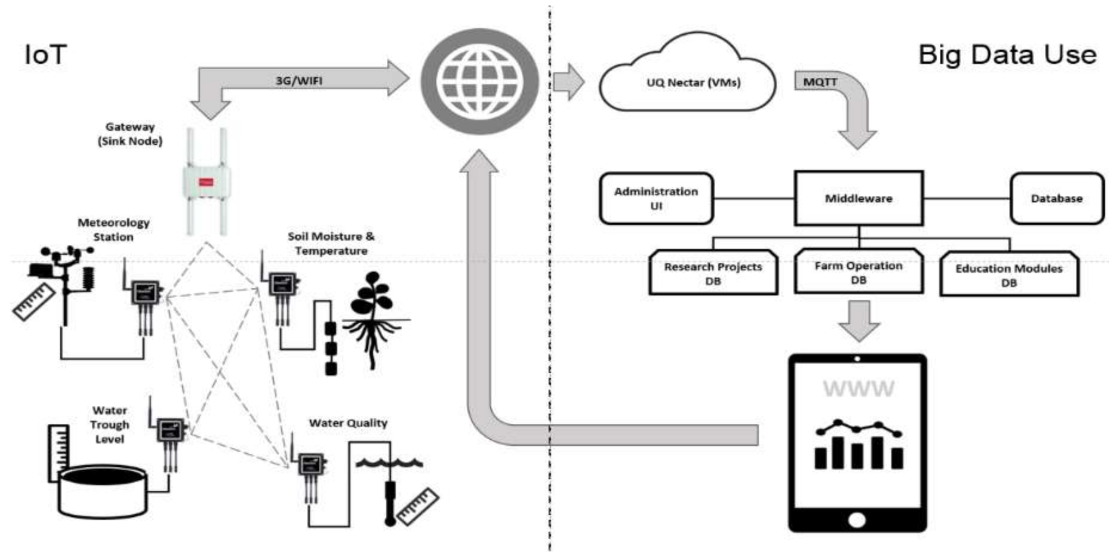
FIGURE 1
WASPMOTE MESH NETWORK TYPOLOGY

FIGURE 2
LIBELIUM SMART AGRICULTURE, WATER, ENVIRONMENT, AND SECURITY MODELS USED IN THE UQ SMART CAMPUS INITIATIVE 2016

The Waspmote technology of Libelium addressed these needs with the added benefit that each node is solar powered (imperative for field-implemented technology), with 12+ hours of backup power and the UQ network link failure protection in place to ensure data integrity. The nodes are autonomous with a smart CPU and all are remote wireless programmable using Arduino-like software (IDE) (Arduino, 2016) which is also compatible with what is currently being taught as part of the Australian High School curriculum.

The IoT system has since been further developed to create a multifaceted web-based interface to the data (Data Dashboard) and problem based learning modules using the real time streaming data from the IoT to produce more engaging and active learning based teaching tools [Figure 3] (Bryceson et al., 2017; Gunesekra et al., 2018).

FIGURE 3
UQGATTON IOT MULTISENSORY MESH NETWORK DEVELOPMENT AND BIG DATA USE



The existing applications include a generic data dashboard app to visualise sensor data in real-time via charts and a mapping tool, and a number of other eLearning applications which can provide course focused visualisations and assessments. As part of the dashboard app, users have the option of downloading raw sensor data (e.g. in CSV format) for use with external applications such as Excel or the statistics package 'R'. Further development in 2018 included a Dairy Dashboard app where daily management data from the UQ Dairy was included (e.g. Feed rations, costs, milk yield/cow, somatic cell count, protein content and fat content/cow etc) to enable managers and students to visualize the dairy herd data to ensure that the dairy is performing appropriately against industry benchmarks.

Further possibilities include applications which will perform business-oriented data analysis and provide more relevant information for the likes of farmers, land managers etc (Bryceson et al., 2017).

Drone Design and Build

The use of satellite data or airborne data has been used in agriculture for many years (Kauth & Thomas, 1976; Drury, 1998; Pinter et al., 2003; Mulla, 2013). This type of data and its use has primarily been seen as a useful way of collecting spatial variability data covering many hundreds of hectares at one time in order to use the knowledge so gained to manage crops, pests, livestock and water more efficiently (Houston & Hall, 1984; Bryceson, 1989; McVicar & Jupp, 1998). The ultimate goal of such data collection being to provide a greater profitability to the users of the data. Unfortunately, the cost of acquisition and processing of this type of remotely sensed data has proven prohibitive to most agricultural managers in the past who have also had the difficulty of finding staff who are adequately trained in processing and using the data.

In the last 7 years much satellite data can now be obtained free through NASA https://earthdata.nasa.gov/ or various National government spatial databases, but there still remains the issue of resolution and useful (for agriculture) revisit frequency. During the same time frame however, there has been an exponential growth in the miniaturisation of electronic equipment that has driven the development and use of small drones (Wang & Tian, 2011; Hunt, 2013). These drones have primarily been either multirotor or fixed wing machines, flying with appropriate sensors payloads in order to obtain low cost imagery at useful revisit frequencies (Anderson, 2014; Van Vark, 2015; Thomasson et al., 2016). Such data can then be used quite easily with readily available software on the equivalently increased computing hardware now available at everyone's fingertips. However, in terms of availability of skilled personnel –

this still lags behind as many agricultural programs are not incorporating remote sensing and associated spatial variability analysis into their curricula.

At UQ this lack of skilled personnel in the use of remote sensing technologies in the agricultural sector is being addressed through the setting up of an Agricultural Remote Sensing Lab, and the development of a third year undergraduate course in Precision Agriculture. Undergraduate students taking the course, or who are doing an Internship or Summer Research project, as well as postgraduate research students are all able to make use of the Lab to actively learn to both design and build drones. Students are taught to fly the drones which carry sensor payloads that provide some standard remote sensing data collection capability (imagery captured in different wavelengths specifically chosen because of their characteristic responses to vegetation biomass, different types of crops, water, soil). Data so collected can then be processed in the Laboratory when the student returns from the field.

There have been a number of design and build projects undertaken e.g. the 'BeneficalBugDrone', the 'NetDrone', the 'WeedDrone' and the 'RFIDDrone' which are described in AusVeg (2015) and Bryceson et al. (2016b). Here the most recent design and build project (the 'UQMiniAgDrone') will be described as will it's use for the above mentioned Precision Agriculture course.

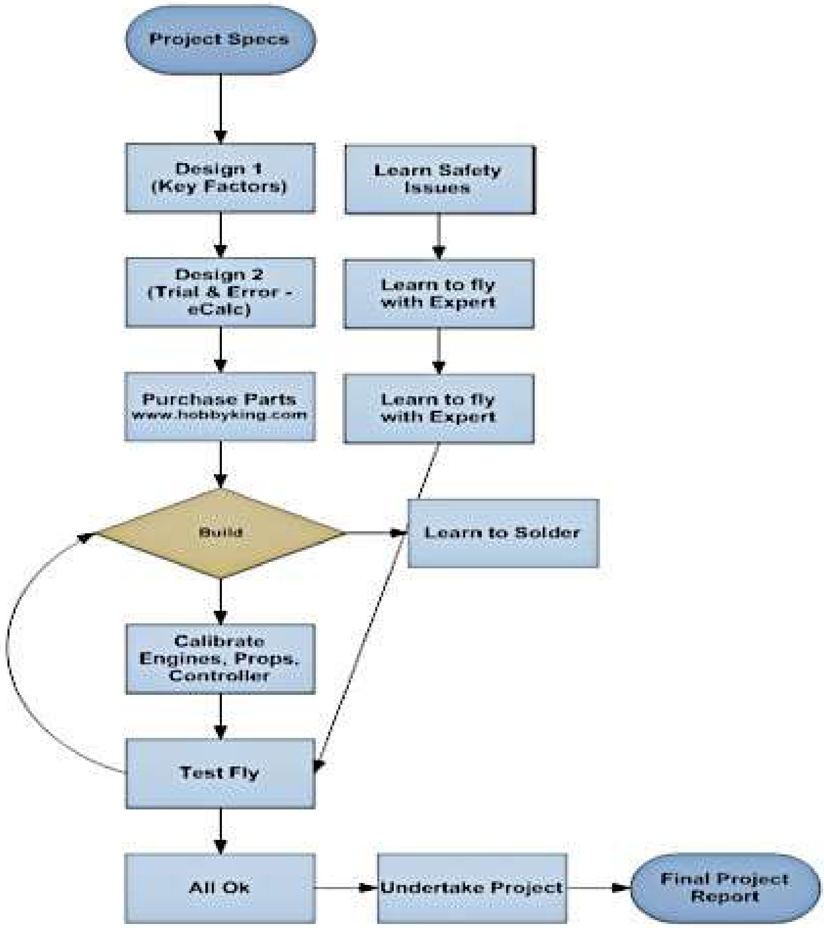
In the design and build projects described here students engage in what is regarded as an active learning process (Prince, 2004), where 'Active Learning' is generally defined as any instructional method that engages students in the learning process and where students are required to do meaningful learning activities and think about what they are doing. Alternatively, the process is often called 'Learn by Doing' (Harvard, 2014) which in these cases described, took took place in the Laboratory and field. The learning process was then brought to a close with the attendant creation of a small report outlining the project specifications, the design and build process undertaken, and the implementation of the drone in a real life project, made explicit the internalized knowledge obtained through the process (Smith, 2001) (see Figure 4 for the schematic for the design process).

When commencing the design and build of a small-medium sized drone or remote controlled aircraft, critical design parameters have to be determined before the start of the design. For example, the physical size of the payload (sensors or cameras or materials to be lifted) and the associated weight to be carried, the selection of a drone frame kit that is size-suitable, and an understanding of local flying conditions such as air temperature and altitude

These initial parameters serve as a basis from which to begin a trial and error process of determining the best possible combination of propeller size, electric motors and the electronic power (battery) needed to lift the payload, while still leaving enough power in reserve to keep the machine stable under stress conditions (e.g. wind) and to maintain a responsive control.

The software program eCalc http://www.ecalc.ch/xcoptercalc.php is a website for UAV enthusiasts, enabling initial designs for unmanned aircraft. Students can enter the types of motors, frame types (normally carbon fibre), propeller length, speed controllers, battery types etc. and instantly get feedback about energy use, flight time, efficiency and projected performance, in order to determine the ideal response control. Students are encouraged to play with these variables until they obtain an acceptable set of design criteria.

FIGURE 4
SCHEMATIC OF DRONE DESIGN AND BUILD PROCESS



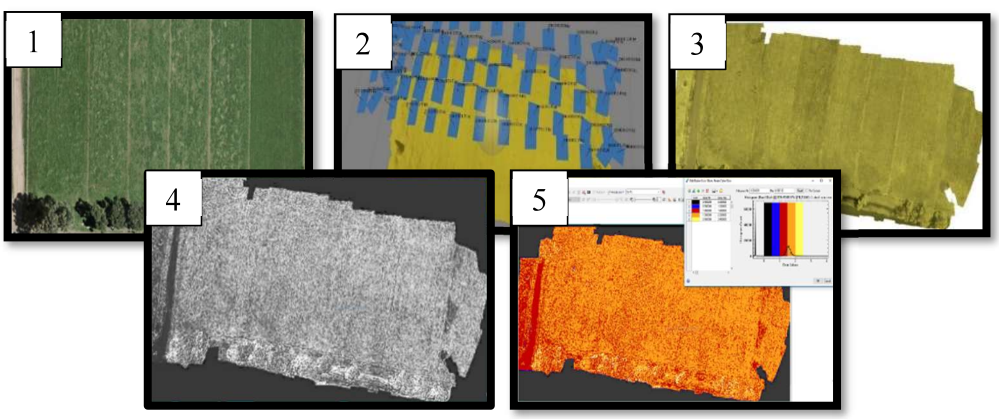
The UQMiniAg drone is the most recent addition to the UQGatton drone "fleet" and has been designed as an aggregate from the collective experience on drone development from research applications. It is designed to be used by students in a tertiary degree, Year 3 Precision Agriculture course. It balances the capabilities of its much bigger brothers, autonomous mission planning and camera payload but it comes with added 'comfort' of a smaller size. [Figure 5].

The size and weight of the drone (<1.3kg) allows multiple units to be deployed in a dedicated case simplifying the use of the drones for practical labs performed under field conditions. In addition, the machine size reduces the risk of any injury should students lose control of it by using lower torque engines. With the standard virtual fence and return to launch safety features, the unit can also be adjusted to "tame" its acceleration curve and limit its operational range effectively reducing risk associated with its kinetic and potential energy.

FIGURE 5
UQMINIAG DRONE

The UQMiniAg Drone was developed to work in conjunction with a WIFI compact camera that takes imagery in two bands RED-NIR and Blue. This imagery serves as the basis from which to perform basic remote sensing training by introducing students to the use of reflected light from the earth's surface as a proxy for to vegetation stress or vigor. The Normalized Vegetation Index (NDVI) (Tucker, 1979), is taught using imagery taken from a mission flown by the student. NDVI gives an index of vegetation greenness or health. This can then be converted to the stocking rate needed for lactating cows in the paddock based on the vegetation health. [Figure 6]. This type of active learning in multidisciplinary domains empowers the student to not only to learn how to use the future tools of the trade, but it also teaches this within context of management decision making on farm, avoiding the all too common complaint of "why I am doing this"?

FIGURE 6
(1) RED GREEN BLUE (RGB) IMAGE CAPTURED USING DRONE AND NOIR CAMERA; (2) MULTIPLE IMAGES MOSAICKED TO FORM A SINGLE LARGE IMAGE; (3) RAW NOIR CAMERA DATA; (4) RAW NOIR DATA PROCESSED FOR NDVI (LIGHT PIXELS MAXIMAL VEGETATION); (5) STOCKING RATE CAPACITY (1-2 ANIMALS/HA) MAPPED FOR PADDOCK



Augmented Reality

There are many definitions of Augmented Reality (AR) – all very similar: a combination of Schueffel (2017) and Rosenberg (1993), produces a solid definition:

> *"Augmented Reality (AR) is a direct or indirect live view of a physical, real-world environment whose elements are "augmented" by computer-generated perceptual information, ideally across multiple sensory modalities, including visual, auditory haptic (touch), somatosensory (sensation), and olfactory (smell) (Schueffel, 2017). The overlaid sensory information can be constructive (i.e. additive to the natural environment) or destructive (i.e. masking of the natural environment) and is spatially registered with the physical world such that it is perceived as an immersive aspect of the real environment (Rosenberg, 1993)."*

Despite the rising use of Augmented Reality in many areas of modern life, AR in education is still new and relatively untested. Dunleavy & Dede (2014) add to the 'Scheuffel plus Rosenberg' definition in relating AR to learning – suggesting there are two forms of AR available to educators:

1. Location aware AR where digital information such as text, graphics, audio, video and 3D models augment the physical environment with narrative, navigation and/or academic information relevant to location (e.g. Layar or Yelp);
2. Vision-based AR where digital information is presented to learners after they point the camera in a mobile device at an object (e.g. QR code or 2D target).

The power for an educator in using AR is, according to Klopfer & Sheldon, (2014) that it: "*...enables students to engage with realistic issues in a context with which students are already connected"*. In other words, students can experience an immersive online learning experience within an existing physical environment which then provides an enhanced learning experience (Bailenson et al., 2008; Salami et al., 2017; Skinner, 2020). This assertion is grounded in two educational theories associated with active and problem based learning: situated learning theory and constructivist learning theory (Dunleavy & Dede, 2014). Situated learning occurs within a specific context with the quality of learning being a result of the experiences gained through interactions among the people, places and objects within that context (Lave & Wenger, 1991). That experiential learning is a critically important mechanism for 'deep' learning, was also identified by Kolb (1984) in his book on the topic: "*Experiential Learning: Experience as a source of learning and development*". The constructivist theory of learning assumes meaning is imposed by the individual rather than existing in the world independently (Vygotsky, 1978).

AR aligns well with both these theories as it enables a situation to be created that puts the learner in a real-world physical and social context while guiding and facilitating participation (Dunleavy & Dede, 2014). For example, AR technology has an ability to render objects that are hard to imagine and turn them into 3D models, then enable interaction with these models making it easier for students to grasp abstract and difficult content. It essentially offers a seamless interaction between the real and virtual worlds (Billinghurst, 2002, Daniela, 2020). Additionally, AR accelerates engagement with students and engagement of students with the content - theoretical knowledge is not enough to obtain proper skills in professional areas. Students should be able to practice and gain hands-on interactive experience in their areas. AR features can help perform 'virtual practice' enabling participants in an AR scenario to acquire both theory and some experience.

The project outlined here (called Affluent Effluent) was a PBL based AR pilot project developed using Wood's (2003) framework to investigate the feasibility of using Microsoft Hololens technology for teaching in the environmental and agricultural space. Our aim for the project was to test student engagement with the technology and appropriate subject matter (in this case waste water management), through using Microsoft's Augmented Reality technology, the Hololens (https://www.microsoft.com/en-au/hololens), and to also test the use of technology and model/simulation for learning about the issue.

The Scenario for Affluent Effluent was that students/players were the owner of 1/2ha "Composite Fish Culture Farm". Their aquaculture business used the pond system for raising fish which has the basic requirement that it be self-sustaining as it grows plants and algae for fish food. Fish are very susceptible to chemicals in water – they need oxygen to survive and anything that influences that, including temperature, needs to be managed very carefully – in other words, fish are complete captives of their environment. Further if the pond is being used as a way to manage effluent from a production situation (eg Piggery or

Feedlot), chemicals such as nitrates, phosphates etc, need to be monitored daily as does the buildup of aquatic weeds.

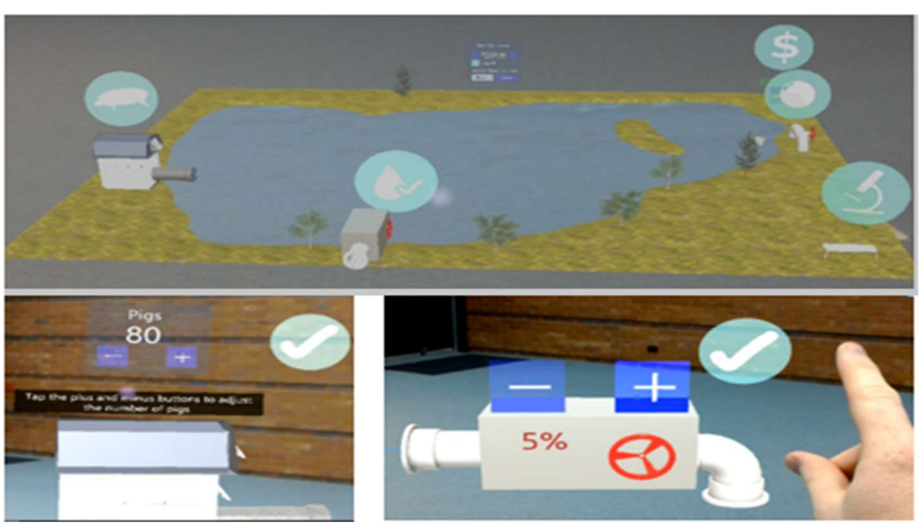
The Learning Objectives for students working in the scenario were that they be able to work either as an *individual* or *collaboratively* in groups to: (i) identify the reasons that led them to believe there may be issues in the pond; (ii) evaluate potential factors that may have contributed to the health of the fish; (iii) identify and describe the process behind the actions they had decided to take to make sure the situation did not happen again; (iv) be able to create a chart to test, record and map the current levels of O2, pH, nutrient content, air and water temperatures against the optimum levels required to maintain a healthy pond.

The Brief for the Augmented Reality (AR) application to enable the evaluation of the objectives of the project**,** was to create a 3D holographic immersive online pond environment with interactive model components that the user could touch and interact with, to demonstrate relationships and key processes. Behind the graphics would run a number of biological and chemical models that enable components of the pond (water quality, fish, plants etc) to change over a time stepped series using either real time data ingress from the field (Gunesekra et al., 2018) or from historical databases. A simple financial model should also be incorporated to take account of the amount of electricity used when pumps and aerators were used. The idea of the AR asset being for students to interact with the holographic model to pull apart the system and make decisions that had real time effect on the model that was being visually displayed. A further aim was for the technology to be used in small and large group teaching either via a single Hololens unit or with multiple Hololens units communicating with each other and with delivery via the Web and Mobile Phone.

The initial AR pilot development process is documented in Bryceson et al., (2018); Bryceson et al., (2019), but briefly, from a learning perspective, the AR simulation needed to be able to let students achieve the learning objectives by linking to an assignment associated with the content which enabled a judgement to be made around the student's ability to identify the problems from the simulation**,** understand the broader issues relating to these problems, and be able to make recommendations for fixing the problem.

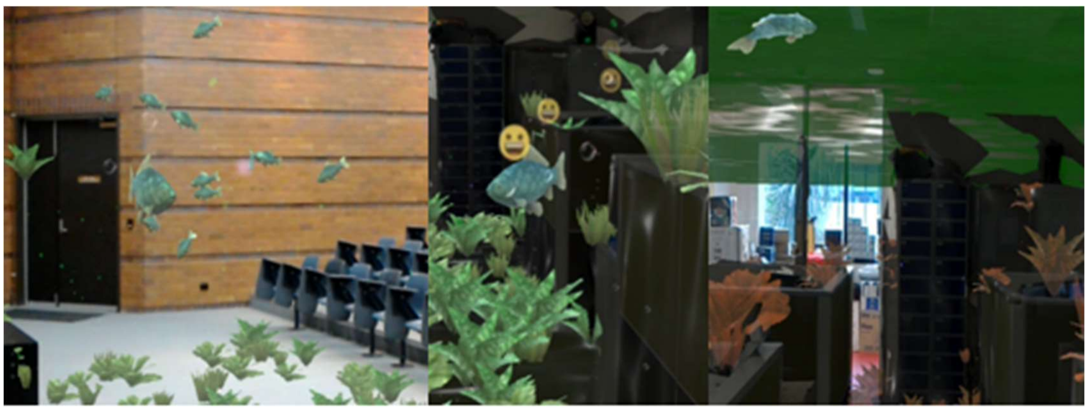
From a teaching perspective, the AR asset had to have appropriate visualisations to create an interesting and immersive learning environment (Christian, 2016)**-** which led to the question of how to visualise things you can't see (e.g. dissolved O2, phosphate cycle)? It was decided that there would be an above water and a below water component. In the above water model (Figure 7), the student could change the number of pigs in the piggery (and thus influence the amount of effluent (nutrients) coming into the pond), turn on and off environmental water pumps (removing water and nutrients from the system), and turn on and off aerators (adding oxygen but also using electricity and building up a bill). They could also view Lab reports on water quality and check their 'bank'.

FIGURE 7
PILOT PROJECT ABOVE WATER MODEL OF POND SITUATED IN LECTURE THEATRE



Below water [Figure. 8], a 3D fish asset would be created that swam around amongst healthy green pond vegetation with a happy emoji and related water movement and breathing sounds when there was enough oxygen, (creating a multisensory aspect), and an unhappy emoji and dying brown plants when there was not. Eventually the fish could die and float to the 'surface' of the pond. An algal bloom would also develop with decreasing oxygen.

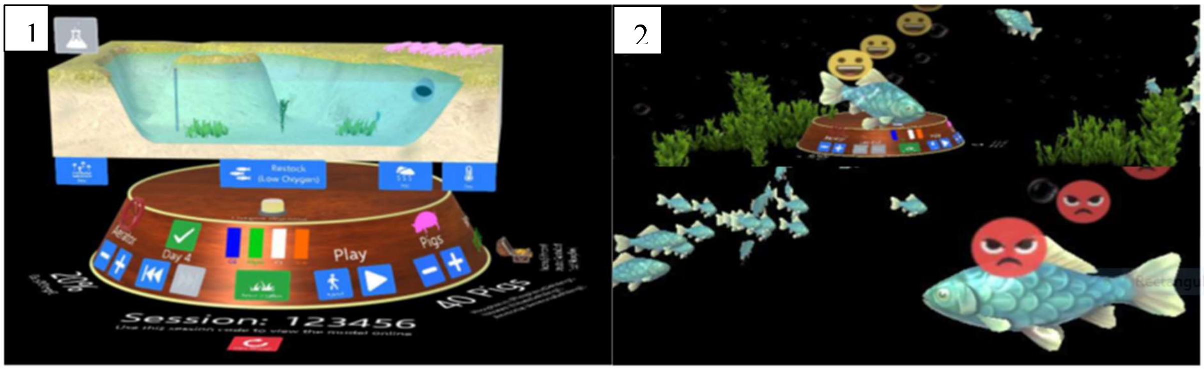
FIGURE 8
PILOT PROJECT BELOW WATER MODEL WITH FISH, EMOJI'S, WATER PLANTS, ALGAL LAYER WITH DEAD FISH



At the end of the development period an informal evaluation of whether the main aims of the project had been achieved was conducted. This was to test student engagement with the technology and appropriate subject matter through using Microsoft's Augmented Reality technology, the Hololens, and to also test the use of technology and model/simulation for learning about the issue. A 100% response rate (n = 11) for "Strongly Like" to all 5 questions relating to the AR tool's engagement and interest questions, was received. However, despite this very positive viewpoint, there were some comments made in relation to the quality of the graphics, the lack of complexity in the decision making capability the application enabled and the need for an illustrated User Guide so that students could prepare prior to using the Application's features.

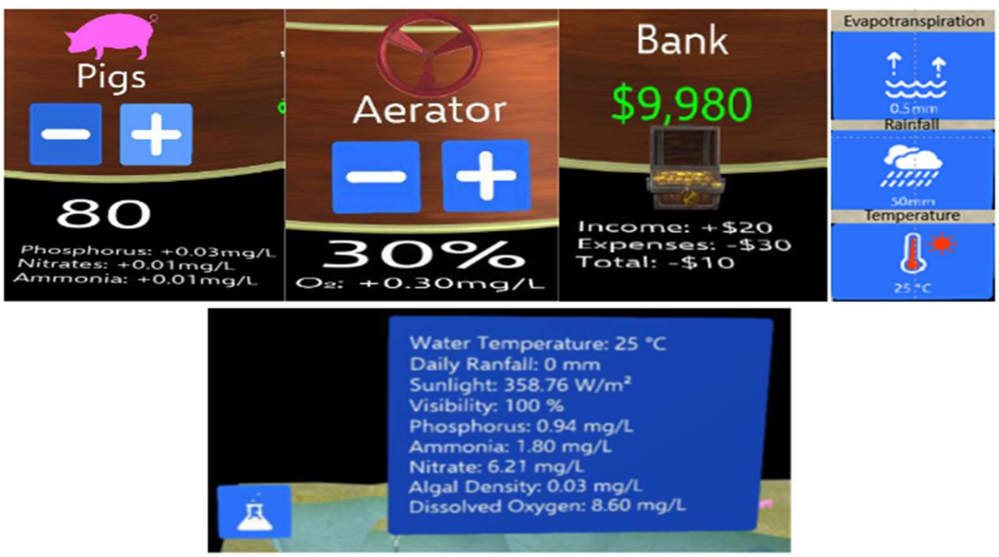
In 2019 the Pilot was upgraded to the current operational system which has included a more complex waste water model underpinning the application - such that decision making by the users (students) could also be more complex dependent on what the Lecturer would like the students to learn – and a substantial upgrade of graphics. A training video was made, a fully illustrated User Guide (Leigh and Bryceson, 2018) developed with instructions on using each feature (e.g. aerator, weather information, number of pigs in the system, bank, time travel etc) and a series of Assignments were also developed that could be used in different courses (e.g. Ecology, Biology, Chemistry, Precision Agriculture, Agribusiness, Statistics). Figures 10 and 11 illustrate some of the upgraded graphics. Additionally the industry partner with which the Project was undertaken (Telstra Purple https://purple.telstra.com.au/) created a professional YouTube Video show off some of the new features during student use which can be viewed here: https://www.youtube.com/watch?v=fpKzNBKMRj4.

FIGURE 9
DESIGN MODE ABOVE WATER



1) Cross section of the pond showing algae and fish – the water colour changes as algae develops and the Rondel on which the new decision making tools are located. 2) Immersive mode below water plants grow/die and fish swim about happily (smiley emoji) or unhappily (red, annoyed emoji) dependant on oxygen content

FIGURE 10
DECISION MAKING TOOLS ENABLING STUDENT TO CONTROL VARIABLES



Left to Right: Number of pigs (proxy for amount of nutrients which = amount/pig added and aligns with Australian pig industry research on effluent content (APL, 2015)); Aerator (amount of oxygen); Bank (income and expenses); Lab report (real time to user running simulation on variables impacting water quality at any point in time).

Additionally, as the application is running, the Hololens logs each decision the Users make and sends the data on 36 linked variables in the model to a website for use – both in real-time, and post session for analysis and after class assessment purposes. Students access their own data on the website with their UQ UserId and Password by identifying the Session Number that is recreated with every new User (Figure 9).

A formal evaluation involving a 10 question survey that covered Engagement, Learning Outcomes and Issues, was undertaken of the revamped application in 2019 with 200 students across the 6 courses identified earlier. The overall results were extremely positive (95% thought it was a good learning tool and that they enjoyed the experience as "something different" and "fun". The results are fully reported in Bryceson et al. (submitted 2020).

From a teaching perspective, the application achieves its goal of engagement and learning and it has proven to address these needs across very different courses in the STEM area enabled by its inclusive design approach and characteristics.

CONCLUSIONS

All three projects developed and used disruptive technologies for agricultural teaching. They have all proven to engage students with the technology, and with subject matter. They have all taken considerable resources (both human and financial) to achieve – and this needs to be further investigated on a cost/benefit basis for any scaling up. This is particularly the case in relation to running a Laboratory dedicated to undergraduate 'Learn by Doing' in the agricultural sector. Such an endeavour requires major funding which is difficult to get from industry funding bodies as this type of lab (as opposed to a 'research' lab) is seen as a teaching asset of the organisation involved and not a research issue. A further finding from all the projects is that there is a need for professional development of lecturers and facilitators in designing the way such technologies can be used in a class and how appropriate assessments can be developed, which are important in contributing or otherwise, to their success. Further research in this area of teacher training in the innovative use of technology needs to be undertaken around 'What' technology is available to be used; 'Why', in terms of pedagogy or student engagement; and 'How' can it be achieved at what cost.

REFERENCES

Anderson, C. (2014, April 23). Relatively cheap drones with advanced sensors and imaging capabilities are giving farmers new ways to increase yields and reduce crop damage. *MIT Technical Review*. Retrieved from https://www.technologyreview.com/s/526491/agricultural-drones

APL (Australian Pork Limited). (2015). *Piggery Manure and Effluent Management and Reuse Guidelines*. Project 2012/1028. Retrieved from http://australianpork.com.au/wp-content/uploads/2013/10/PMEG_2014_14_lr.pdf

Archer, W., Garrison, R., & Anderson, T. (1999). Adopting Disruptive Technologies in Traditional Universities: Continuing Education as an Incubator for Innovation. *Canadian Journal of University Continuing Education*, *25*(1), 13-30.

Arduino Software. (2016). Retrieved from https://www.arduino.cc/en/Main/Software

AusVeg. (2015, March/April 10-12). When Horticulture meets futuristic technology, the possibilities are tremendous. *Vegetable Australia, Magazine*. Retrieved from https://ausveg.com.au/app/data/publications/VA/VA-MarApr2015.pdf

Bailenson, J.N., Yee, N., Blascovich, J., Beall, A.C., Lundblad, N., & Jin, M. (2008). The Use of Immersive Virtual Reality in the Learning Sciences: Digital Transformations of Teachers, Students, and Social Context. *Journal of the Learning Sciences*, *17*(1), 102 141. DOI: 10.1080/10508400701793141

Billinghurst, M. (2002). *Augmented Reality in Education. New Horizons for Learning - Technology in Education*. Seattle, WA.

Bourlakis, M., Vlachos, I., & Zeimpekis, V. (2011). *Intelligent Agri-food Chains and Networks.* Oxford, Blackwell-Wiley.

Bryceson K.P., Navas Borrero, A., & Gunasekera, K. (2016a, July). The Internet of Things (IoT) - Smart Agriculture Education at The University of Queensland. *Proceedings of Edulearn16, 8th International Conference on Education and New Learning Technologies* (pp. 8036-8044). Barcelona, Spain.

Bryceson, K.P. (1989). The use of Landsat MSS data to determine the locust eggbeds of locust eggbeds in the Riverina region of New South Wales, Australia. *International Journal of Remote Sensing*, *10*(11), 1749-1762.

Bryceson, K.P. (2006). *'E' Issues in Agribusiness: The What, Why, How* (p.384). CABI Publishing, UK.

Bryceson, K.P. (2007, October 15). SECI, BA, ESCI and VAG – Linking Models of Knowledge Acquisition, ELearning and Online Immersive Worlds to Create an Innovative Learning Environment. In *World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2007* (pp. 2365–2372). Retrieved from https://learntechlib.org/p/26712/

Bryceson, K.P. (2019, June). Disruptive Technologies in Agricultural Education. *Proceedings of 5th International Conference on Higher Education Advances (HEAd'19)* (pp. 315-322). Universitat Polit`ecnica de Val`encia, Val`encia, Spain. DOI: http://dx.doi.org/10.4995/HEAd19.2019.8957

Bryceson, K.P., & Yaseen, A. (2018). Smart technologies: disruptive technologies and the agrifood industry: fit for practice? In O. Bak (Ed.), *E-Business and Supply Chain Integration: Strategies and Case Studies from Industry* (Ch. 2, pp. 27-50). Kogan Page, UK.

Bryceson, K.P., Borrero, A.N., & Vasuian, F. (2017). Internet of Things (IoT), PBL and 3D Holographic modelling for Smart Agriculture Education at The University of Queensland. In H. Partridge, K. Davis, & J. Thomas (Eds.), *Me, Us, IT! Proceedings ASCILITE2017: 34th International Conference on Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education* (pp. 208-215). Retrieved from http://2017conference.ascilite.org/wp-content/uploads/2017/11/ASCILITE-2017-Proceeding.pdf

Bryceson, K.P., Grondahl, L., Sarwar, S., & Leigh, S. (2020). Augmented Reality as a Teaching Tool in an Integrative STEM environment: A Case Study of Water Management. *Higher Education Journal.*

Bryceson, K.P., Navas Borrero, A., Camilleri, C., & Vasuian, F. (2016b, July). Small Quadcopter Drones as Educational Tools in Agriculture at the University of Queensland, Australia. *Proceedings of EDULEARN16, 8th International Conference on Education and New Learning Technologies* (pp. 8052-8060). Barcelona, Spain.

Bryceson, K.P., Vallely, E., & Vasuian, F. (2018, July). Affluent Effluent Waste Water Management – a Pilot Project using Augmented Reality for student engagement in agricultural education. *Proceedings of EDULEARN18, 10th International Conference on Education and New Learning Technologies* (pp. 5751-5760). Palma, Spain.

Christensen, C.M., & Overdorf, M. (2000). Meeting the challenge of disruptive change. *Harvard Business Review*, *78*, 66-76.

Christian, M. (2016, December). *How Can Immersive Technologies Improve Learning in Higher Ed?* Tech Decisions. Retrieved from https://techdecisions.co/mobility/can-immersive-technologies-improve-learning-higher-ed/

Daniela, L. (2020). *New Perspectives on Virtual and Augmented Reality: Finding New Way to Teach in a Transformed Learning Environment* (p.322). London, Routledge. https://doi.org/10.4324/9781003001874

Drury, S.A. (1998). A short history of remote sensing. In S.A. Drury (Ed), *Images of the earth: a guide to remote sensing*. Oxford University Press New York, NY.

Dunleavy, M., & Dede, C. (2014). Augmented Reality Teaching and Learning. In J.M. Spector, M.D. Merrill, J.E. & M.J. Bishop (Eds.), *Handbook of Research on Educational Communications and Technology* (pp. 735-745). Springer, New York.

Flavin, M. (2012). Disruptive Technologies in higher education. *Research and Learning Technology Supplement: ALT-C 2012 Conference Proceedings* (pp. 102- 111).

Garrison, D.R., & Kannuka, H. (2004). Blended Learning: Uncovering Its Transformative Potential in Higher Education. *Internet and Higher Education*, *7*(2) 95-105.

Gartner IT Glossary. (2016). Retrieved from http://www.gartner.com/it-glossary/internet-of-things/

Gunasekera, K., Navas Borrero, A., Vasuian, F., & Bryceson, K.P. (2018). Experiences in building an IoT infrastructure for agriculture education. *Procedia Computer Science* (pp. 155-162). DOI: 10.1016/j.procs.2018.08.161

Hall, A. (2016). *Thoughts about what disruptive innovation means for agriculture research organisations*. Food Systems & Innovation. Retrieved from https://foodsystemsinnovation.org.au/blogs

Harvard, J. (2014, May-June). Learning by Doing. *Harvard Magazine*, pp. 18-20.
Houston, G., & Hall, F.G. (1984). Use of satellite data in agricultural surveys. *Communications in Statistics - Theory and Methods*, *13*(23), 2857-2880. http://dx.doi.org/10.1080/03610928408828868
Hunt, D. (2013, July 31). *The evolution of miniaturization within UAV connector technology*. Military Embedded Systems. Retrieved from http://mil-embedded.com/articles/the-UAV-connector-technology
Kauth, R.J., & Thomas, G.S. (1976). *The Tasselled Cap. A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat*. LARS Symposia. Paper 159. Retrieved from http://docs.lib.purdue.edu/lars_symp/159
Kim, Y., Evans, R.G., & Iversen, W.M. (2008). Remote sensing and control of an irrigation system using a distributed wireless sensor network. *IEEE Transactions on Instrumentation and Measurement*, *57*, 1379-1387.
Klopfer, E., & Sheldon, J. (2014, Winter). Augmenting your own reality: student authoring of science-based augmented reality games. *New Directions for Youth Development*, *128*, 85-94.
Kolb. (1984). *Experiential Learning: Experience as a source of learning and development*. Prentice Hall. Englewood Cliffs, NJ.
Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation.* Cambridge University Press, Cambridge.
Lehmann, R.J., Reiche, R., & Schiefer, G. (2012). Future Internet and the Agrifood sector: state-of-the-art in literature and research. *Computers and Electronics in Agriculture*, *89*, 158-174.
McVicar, T., & Jupp, D. (1998). The Current and Potential Operational Uses of Remote Sensing to Aid Decisions on Drought Exceptional Circumstances in Australia. *Agricultural Systems*, *57*(3), 399-368.
Millar, C., Lockett, M., & Ladd, T. (2018). Disruption: Technology, Innovation and Society. *Technology Forecasting and Social Change*, *129*, 254-260.
Mulla, D. (2013). Twenty five years of remote sensing in precision agriculture. *Biosystems Engineering*, *114*, 358-371.
Nat West. (2019). *Farming: Inspiring young hearts and minds*. Report in the Nat West Bank Agriculture Hub. Retrieved from https://natwestbusinesshub.com/articles/farming-inspiring-young-hearts-and-mindsp.
Pinter, P.J., Jr., Hatfield, J.L., Schepers, J.S., Barnes, E.M., Moran, S.M., Daughtry, C.S.T., & Upchurch, D.R. (2003). Remote Sensing for Crop Management. *Photogrammetric Engineering & Remote Sensing*, *69*(6) 647–664.
Prince, M. (2004). Does active learning work? A review of the research. *Journal of Engineering Education*, *93*(3), 223-231. Full text available through MIT Libraries.
Rosenberg, L.B. (1993). Virtual Fixtures: Perceptual Overlays for Telerobotic Manipulation. In *Proceedings of the IEEE Annual International Symposium on Virtual Reality* (pp. 76–82).
Sagenmüller, I. (2017). *Four Disruptive Education technologies poised to change higher learning*. Retrieved from https://www.u-planner.com/blog/disruptive-education-technologies-poised-to-change-higher-learning
Salmi, H., Thuneberg, H., & Vainikainen, M-P. (2017). Making the invisible observable by Augmented Reality in informal science education context. *International Journal of Science Education*, Part B, *7*(3), 253-268. https//doi.org/10.1080/21548455.2016.1254358
Schmidt, H.G. (1983). Problem-based learning: Rationale and description. *Medical Education*, *17*(1), 11–6.
Schueffel, P. (2017). *The Concise Fintech Compendium.* Fribourg School of Management, Fribourg, Switzerland.
Sharples, M. (2003). Disruptive devices: mobile technology for conversational learning. *International Journal of Continuing Engineering Education and Lifelong Learning*, *12*(5/6), 504-520.

Skinner, C. (2020). Flash Flood!: A SeriousGeoGames activity combining science festivals, video games, and virtual reality with research data for communicating flood risk and geomorphology, *Geoscience Communication*, *3*, 1–17. https://doi.org/10.5194/gc-3-1-2020

Smith, E.A. (2001). The role of tacit and explicit knowledge in the workplace. *Journal of Knowledge Management*, *5*(4), 311-321.

Stočes, M., Vaněk, J., Masner, J., & Pavlík, J. (2016). Internet of Things (IoT) in Agriculture - Selected Aspects. *AGRIS On-line Papers in Economics and Informatics*, *8*(1), 83-88. DOI:10.7160/aol.2016.080108

Thomasson, A.J., Shi, Y., Olsenholler, J., Valasek, J. Murray, S.C., & Bishop, M.P. (2016). Comprehensive UAV agricultural remote-sensing research at Texas A M University. *Proceedings Volume 9866, Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping*. Event: SPIE Commercial + Scientific Sensing and Imaging. Baltimore, Maryland, United States. https://doi.org/10.1117/12.2234052

Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sensing of the Environment*, *8*, 127-150.

Van Vark, C. (2015, December 26). *Drones set to give global farming a makeover*. The Guardian.com. Retrieved from http://www.theguardian.com/profile/caspar-van-vark

Vellidis, G., Tucker, M., Perry, C., Kvien, C., & Bednarz, C. (2008). A real-time wireless smart sensor array for scheduling irrigation. *Computers and Electronics in Agriculture*, *61*, 44-50.

Vygotsky, L.S. (1978). *Mind in society: The development of higher psychological processes.* Harvard University Press, Cambridge, Massachusetts.

Wang, H., & Tian, L. (2011). Development of a low-cost agricultural remote sensing system based on an autonomous unmanned aerial vehicle (UAV). *Biosystems Engineering*, *108*(2), 174-190.

Wood, D. (2003). Problem Based Learning. In P. Cantillon, L. Hutchinson, & D. Wood (Eds.), *ABC of Learning and Teaching Medicine* (Ch 3, pp. 8-11). BMJ Publishing Group: London, UK.

Zawawi, A.E., & Ibrahim, A. (2012). *Using Zigbee to Build a Web-Based DCS System*. IEEE Power and Energy Society General Meeting. https//doi.org/10.1109/PESGM.2012.6343966