Virtual Reality in Biology: could we become virtual naturalists?

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Abstract

Virtual Reality (VR) and derived technologies which mixes the real world with some aspect of virtuality (e.g., Augmented Reality, Mixed Reality) has emerged as a powerful allied in education. Recent technological advances made Virtual and Mixed Reality (VMR) accessible at our fingertips. However, only recently VMR has been explored for the teaching of Biology. In this review, we describe how VMR applications are useful in Biology education, discuss the caveats related to VMR use that can interfere with learning, and look into the future of VMR applications in the field. We then propose a conceptual model for the future of VMR in Biology, which envisage to combine VMR with Machine Learning and Artificial Intelligence to provide unprecedented ways to visualise how species evolve in self-sustained immersive virtual worlds, thereby transforming VMR from an educational tool to the centre of biological interest. This conceptual paper aims to stimulate debates on how new technologies can revolutionise teaching and learning across scenarios, which can be useful for improving learning outcomes of biological concepts in face-to-face, blended, and distance learning programmes.

Keywords: Darwinian theory; new technology; evolutionary biology; immersive reality; evolving algorithm
With increasing computational power, technologies that were costly or impossible to implement in the past have now become accessible in laptops and mobile phones (Kish 2004; Waldrop 2016). These technologies are now revolutionising the ways we interact with the world, how we learn, and how we teach (Veletsianos 2010). Virtual and Mixed Reality (VMR, see Box 1 for terminology) is one of these technologies which has gained increasing attention in the academic and teaching communities (Mazuryk and Gervautz 1996). In fact, over the last decade, there has been an exponential increase in the publication of papers in topics involving Virtual and Mixed Reality in Education (Fig 1a). VMR can be defined as an alternate world filled with computer-generated entities that interact with human sensory and motor systems to cause a sense of ‘presence’ (psychological state) in the subject through the use of an ‘immersive’ technology (i.e., technology that simulates an environment that is not necessarily real) (Yoh 2001). Presence can be defined as ‘a state of dissociation from reality in which people feel the subjective experience of existing in the digital environment (Slater 2003).’ Although presence and immersion have been used interchangeably (Barbot and Kaufman 2020), experiences that increase presence do not necessarily increase immersive feelings, and vice versa [see meta-analysis by (Cummings and Bailenson 2016)], suggesting that, although these terms refer to the feeling of ‘being there’, they are not necessarily equivalent. Nevertheless, both are important in VMR applications. According to the Oxford dictionary, Virtual Reality is defined as ‘images and sounds created by a computer that seem almost real to the user, who can interact with them by using sensors’, which highlights that presence and immersion are key aspects of virtual reality [see e.g., (Lombart et al. 2020)]. According to Milgram et al. (1995)’s taxonomy, immersive experiences are achieved through a complex continuum in reproduction fidelity of both the real and virtual environments, whereby the limitations of approaches as well as hardware (e.g., devices and displays) can influence the degree of immersive experience and presence available to the user (Milgram et al. 1995). Note, however, that the feeling of presence and immersion may not necessarily be the ultimate goal of VMR technologies [(Milgram et al. 1995); but see (Sheridan 1992; Robinett 1992)], although the increasingly more realistic displays can eventually result in one feeling complete immersion and presence (Naimark 1991).

VMR has been around for decades, and it thought to have its origin when, in the 1960s, Morton Heilig created one of the first immersive multi-sensory simulator that included stimuli such as sound, scent, wind and vibration (called ‘Sensorama’) (Heilig 1962; Mazuryk and Gervautz
Ever since, VR technology has advanced significantly to the point that today there exists many platforms for creating as well as experiencing VMR applications [e.g., (Ledermann and Schmalstieg 2005; Jerald et al. 2014; Wexelblat 2014)]. In the last decade, the use of VMR in teaching and learning has increased dramatically, and spans across a variety of subjects (Hoffman and Vu 1997; Mikropoulos and Natsis 2011; Davies, Crohn, and Treadgold 2019; Makransky, Thisgaard, and Gadegaard 2016), including biology (Makransky et al., 2016; Shim et al., 2003; Shim, Kim, & Park, 2000). A meta-analysis of sixteen studies has shown that VMR surgical simulators decrease the time to complete surgical procedures, suggesting a more efficient surgical skill acquisition (Haque and Srinivasan 2006). Furthermore, VMR improves the learning of tasks that require spatial and visual memory, observation, as well as control of emotional responses in stressful conditions (Jensen and Konradsen 2018). Importantly, autistic children have been described as having positive engagement with VMR applications in educational settings (Strickland et al. 1996; Kandalaft et al. 2013), suggesting that VMR can be used in a wide range of contexts and function as an inclusive tool for the education of students with special needs. Therefore, VMR has the potential to become an important educational tool in our century (Hoffman and Vu 1997).

In this conceptual paper, we first provide a mini-review of VMR applications that are changing teaching and learning in biology. Next, we discuss the potential caveats associated with misuses of VMR applications and discuss how VMR use can hinder (rather than help) teaching and learning. We believe this balanced view is important to guide future developments in the field. Lastly, we look into the future of VMR technology and discuss the directions in which VMR developments can take us, revolutionising teaching of important principles of nature. We propose a conceptual model of how VMR can act as an independent, self-sustained virtual experimental world (which we call ‘BioVR’). For brevity, we use a broad definition of VMR which includes all virtual types of applications, from Augmented Reality (AR), Mixed Reality (MR) through to Virtual Reality sensu stricto (see Box 1). This paper’s main objectives are to provide a balanced overview of the costs and benefits of using VMR into the classroom for teaching evolutionary biology concepts and stimulate discussion about the future of educational technology by proposing a conceptual innovative application of VMR (what we called ‘BioVR’) in the classroom for an effective teaching of evolutionary biology that can encapsulate three domains of learning (i.e., cognitive, affective, and psychomotor). It is equally important to mention that this paper does not aim to provide a step-by-step guideline for the implementation of VMRs in the classroom, as these guidelines are available elsewhere (see our...
Having defined the scope of this conceptual paper, we hope that this paper will help guide future developments in VMR applied to biology in a constructive manner, stimulating collaborations across fields (e.g., Computer Science and Gaming) to develop new teaching technologies to facilitate and enhance students’ learning experiences.

**Fig 1 – VMR increasing importance in academic and educational context.** (a) Web of Science Topic query of publications (left) and citations (right) that involves VMR and education (orange) and VMR and biology (red). WoS searches were conducted on 12-May-2020 with search term queries ‘(virtual AND augmented) reality AND education’ or ‘(virtual AND augmented) reality AND biology’. For each search, reviews and proceedings of conferences were excluded. In total, there were 6,443 and 133 papers that fitted the selection criteria, respectively. (b) Schematic overview of the potential for VMR to impact Biology. On one hand, VMR has increasingly been used for teaching of a variety of topics within Biology. As technology advances, it may be possible to combine other cutting-edge technologies such as Machine Learning and Artificial Intelligent to create a self-sustained evolving virtual world (BioVR) that allows us to gain insights into biological processes.
VMR uses in Biology education

While VMR in education has gained exponential attention of the academic community, VMR in biology has advanced at a slower pace, comprising ~ 5% of academic publications in the field (Fig 1a). Nonetheless, VMR has gained important applications in both secondary and tertiary education biology courses (Makransky, Thisgaard, and Gadegaard 2016; Poland, Baggott la Velle, and Nichol 2003; de Jong, Linn, and Zacharia 2013; Thisgaard and Makransky 2017). A number of VMR applications attempt to reproduce the laboratory environment to students with otherwise no access to laboratory facilities, with demonstrated benefits over traditional lectures [see e.g., Labster (Bonde et al. 2014)]. Other VMR applications were designed to give the students an immersive experience of more specific biological processes such as cell structure (McClean, Slator, and White 1999), spatial orientation (Moritz and Meyer 2004), and vision formation in animals (Gochman et al. 2019). Students report higher engagement and learning outcomes with immersive experiences offered by VMR applications, which is encouraging for the use of VMR in biology education (Makransky, Terkildsen, & Mayer, 2019; Makransky et al., 2016; Mikropoulos, Katsikis, Nikolou, & Tsakalis, 2003; Mikropoulos & Natsis, 2011; Shim et al., 2003) (Fig 1b). For example, Moritz and Meyer (2004) designed an immersive interactive VMR platform for visualisation and teaching of conformation and geometry of protein crystallographic structures, whereby the test group was able to identify characteristics and regions in the samples that were obfuscated in non-immersive programs (Moritz and Meyer 2004). Thus, innovative curricula that harness the power of new technologies can provide significant benefits to the teaching and learning of biology (Eastwood and Sadler 2013; Sadler et al. 2015).

VMR applications could help learning and teaching of ecology by simulating field expeditions in which students have to identify plants and/or animals in virtual reality, as in non-immersive virtual field trips developed previously [e.g., (Spicer and Stratford 2001; Dunleavy, Dede, and Mitchell 2009)]. Students have in fact reported that non-immersive virtual field trips provide a useful complement to the real field trip and could be a powerful tool to prepare and revise real field trips (Spicer and Stratford 2001). This could also complement units of taxonomy of plants and animals as well as provide virtual field experience to the student prior to the real task, thereby amalgamating students’ learning experience. In VMR, immersive scenarios could include representative environments from different ecosystems (e.g., Amazon rainforest,
tundra, desert) in which the aim is to identify the greater number of plant species as well as the morphological traits that are shared amongst species.

It is important to mention that virtual systems have been developed to explore all aspects of biology education. For instance, pervious digital material has been designed for teaching and learning of astrobiology [for instance in the Habitable Worlds platform (Horodyskyj et al. 2018)], although not yet in the fully immersive platform of VMR. Habitable Worlds allows students to experience a inquiry-driven learning environment designed to enhance students’ learning outcomes on science through observation and modelling of virtual systems (Horodyskyj et al. 2018). The results are promising as more than 70% of students had grades average or higher, and student engagement significantly increased compared to benchmark. As such, Habitable Worlds provides some guidelines for the design of digital platforms that could be transferable to VMR systems, including automated feedback tailored to the students’ needs and student-educator interactions (both in real-time and in forums) (Horodyskyj et al. 2018). It will be interesting for future developments of Habitable Worlds to expand the educational content from astrobiology to other subjects within biology, as well as to include VMR experience and compare the performance of students with traditional versus immersive platforms.

The potential misuses of VMR

As for any new technology, we are still discovering the limitations of VMR applications as educational tools. VMR applications are attractive because they contain a wide variety of sensory stimuli that give the participant a sense of presence. However, too many stimuli – such as colours, shapes, characters, movement – can distract the participant and have detrimental effects on learning, a phenomenon that has been acknowledged in the literature and commonly referred to as cognitive overload (Whitelock et al. 2000). A recent study has shown that university students learned less and experienced higher cognitive overload when they experienced a science lab in a fully-mounted VMR headset as oppose to the VMR scenes played on 2D displays, in spite of higher feeling of presence in the VMR scene as opposed to the 2D screen display (Makransky, Terkildsen, and Mayer 2019). This suggests that, in some cases, the very same attributes that make VMR attractive can make VMR applications ineffective. Nonetheless, it is possible to mitigate cognitive overload by controlling the information flow that students are exposed to as part of the design of the environment, the tasks needed to be completed, as well as the degree of interactivity with the environment at any given
point in time [e.g., (Dorneich et al. 2003; Wang et al. 2019; Andersen et al. 2016; Bharathan et al. 2013)]. Other potential negative effects of VMR applications are motion sickness and dizziness caused by the immersive experience, which can preclude appropriate understanding of the learning material and hamper students’ achievement of learning outcomes (McCauley and Sharkey 1992; Regan and Price 1994; Ohyama et al. 2007; Davis, Nesbitt, and Nalivaiko 2015; Palmisano, Mursic, and Kim 2017). For instance, the perception of angular and linear accelerations cause intense motion sickness both in short and long exposure to VMR applications (McCauley and Sharkey 1992; LaViola Jr 2000; Saredakis et al. 2020; Sharples et al. 2008). Yet, recent studies have demonstrated that motion-sickness can be mitigated or eliminated through appropriate use of VMR design (e.g., immersiveness of the application) and suitable hardware (e.g., display type) [see e.g., (Mittelstaedt, Wacker, and Stelling 2018; Mittelstaedt, Wacker, and Stelling 2019; Weech, Kenny, and Barnett-Cowan 2019)]. Interestingly, a recent meta-analysis suggested that the feelings of presence and motion-sickness likely trade-off – with higher presence resulting in lower motion-sickness (Weech, Kenny, and Barnett-Cowan 2019), supporting the idea that motion-sickness can be mitigated (or eliminated) with thoughtful design and user-experience.

Recent literature provides comprehensive lists of fundamental characteristics of 3D virtual environments and general features that can be adjusted to increase students’ engagement and learning in virtual systems [see e.g., (Dalgarno and Lee 2010; Lindgren et al. 2016; O’Connor and Domingo 2017)]. In fact, a series of learning affordances have been identified, which we reproduce in Table 1, that have positive influence on students’ engagement with virtual applications and can ultimately enhance learning (Dalgarno and Lee 2010); these learning affordances are revisited in our BioVR model (see below). These affordances highlight the benefits of using VMR applications in the classroom. Here, our point is to reiterate the importance of careful design and testing of new VMR applications prior to implementation in the classroom in order to mitigate potential cognitive overload and/or motion sickness, which could significantly hamper VMR’s educational potential and the achievement of learning affordances (Dalgarno and Lee 2010). Future studies will provide more detailed evidence-based guidelines to build effective VMR applications that maximise educational potential while minimising negative effects of VMR misuse (Dunleavy, Dede, and Mitchell 2009; Akçayır and Akçayır 2017).

Bio-inspired systems and the rise of artificial evolution
The parallels between natural and artificial evolutionary systems have long been recognised and explored. While few artificial life systems exist, perhaps the most famous example comes from the work of Thomas Ray and the ‘Tierra’ system (Langton 1986; Langton 1997; Lehman, Clune, and Misevic 2018; Ray 1992). The Tierra system simulates artificial life in self-replicating, evolving entities (‘algorithms’) confined within virtual computer spaces, whereby the entities can be considered as uni- or multi-cellular entities that experience errors in replication analogous to mutations in biological reproduction (Ray 1992; Thearling and Ray 1994; Ray 1994). Instead of solar energy and natural resources as in biological systems, artificial entities compete for central processing unit (CPU) and memory space [analogous to energy and spatial resource, respectively [as described in (Ray 1992)]. As a result, artificial Tierra entities become progressively more adapted to exploit one another in order to gain advantage over the use of CPU and memory (Ray 1992; Thearling and Ray 1994; Ray 1994; Ray and Xu 2001). The outcome of this self-sustained virtual evolutionary world is remarkable given that the system evolves differences in entity sizes, ecological specialisation (e.g., parasites) and population dynamics processes (e.g., extinction) (Ray, 1992, 1994; Ray & Xu, 2001; Shao & Ray, 2010). This provides an unprecedented study case to compare and understand how different shapes and forms emerge through evolutionary processes. However, visualisation of evolution in the Tierra system is not straightforward and largely inaccessible to a broader audience due to the highly technical language underlying the system. This poses a significant barrier to biologists with limited computational expertise and it is, to some extent, visually unappealing for students of biological sciences and related disciplines. Consequently, it is difficult (though not impossible) to use artificial model systems such as Tierra as an effective educational tool in the classroom while keeping the attention span and interest of students.

Can VMR and Artificial Intelligence (AI) revolutionise artificial evolutionary systems?

As discussed above, VMR is a powerful and appealing educational technology to teach biology. This is because students and educators respond rationally as well as emotionally to the educational material in the immersive experience, which can accentuate learning (de Jong, Linn, and Zacharia 2013; Thisgaard and Makransky 2017; Dunleavy, Dede, and Mitchell 2009; Harley et al. 2016; Riva et al. 2007). Thus, VMR can be an appropriate way to overcome accessibility problems of artificially evolving systems while increasing visual appealing to specialists and general audience.
The technological advances that allowed VMR to become an accessible tool has also allowed for the feasibility of powerful statistical models of Machine Learning and Artificial Intelligence (AI). Machine Learning are algorithms that process and learn with huge amounts of data in order to perform a task without necessarily being explicitly programmed to do so (Bishop 2006). AI attempts to simulate human intelligence in machine systems; this includes machine learning but also (bio-inspired) robotics, ethics and philosophy associated with AI development (Russell and Norvig 2002). Importantly, AI advances have recently demonstrated that machines can learn from data beyond human capabilities (Chouard 2016; Gibney 2016). Furthermore, a new area on the interface between VMR and AI aims to integrate AI to entities in VMR (Luck and Aylett 2000; Laukkanen et al. 2004; Augusto et al. 2013). As a result, a key question emerges: can we combine Machine Learning and AI with VMR to create a self-sustained evolving virtual world (a ‘BioVR’)? If so, why should we combine VMR with AI? The answer to the first question is, in our opinion, a sounding ‘yes’. We strongly believe that future technological advances have the potential to create an immersive virtual world that reproduces the forces of evolution, which can allow us to visualise and measure how species have evolved, how ecosystems are formed, how species adapt to their environment, how we can anticipate effects of adverse climatic conditions across ecosystems in our changing world. In a sense, we could become ‘virtual naturalists’ that explore evolution in a simulated (virtual) world in the same sense that naturalists explore the natural (real) world. The learning benefits are unprecedented given that students can experience inaccessible and inhospitable environments, observe evolution, adaptation, trophic interaction, parasitism and many more biological processes without stepping outside the classroom (Learning affordance #2; Table 1). Moreover, the freedom given to the students within these BioVRs forms the perfect ground for inquiry-based learning and engagement, where the students will observe and explore the environment, measuring and experiencing the virtual environment to inquiry about the underlying virtual biological phenomena (Horodyskyj et al. 2018) (Learning affordance # 3, Table 1). Ultimately, the BioVR could be used to supplement and stimulate collaborative learning tasks, where students may compare and contrast the evolution of individual BioVR evolutions and identify similarities (e.g., parallel evolution) and divergences (e.g., specialisation traits) between virtual entities (Learning affordance #5; Table 1). The BioVR could then eliminate the need for complex computational expertise (at least from the users’ point of view) and provide a fully immersive, artificial world upon which entities evolve following basic principles of biological evolution in our and other planets, while students can explore the environment and learn from their own virtual experience.
Practical implementation of BioVR by experts could in theory be achieved through the following steps:

1. Simulate an artificial ‘planet’ whereby entities will interact, compete, and evolve. In this artificial planet, the ‘biotic’ rules are established, such as the basic environmental conditions (e.g., temperature), habitat (e.g., marine vs terrestrial landscapes), resource distribution and so on [similar in concept to the ‘soup’ in Tierra and the concept of virtual environments in (Luck and Aylett 2000)].

2. Design the ancestor entity, defining the rules of reproduction, mutation, and ecological interactions that govern the outcomes of interactions between entities as well as with the environment in the planet. This will likely require that the entities follow theoretical models that relate trait expression and fitness, as well as fitness changes over lifetime and through generations [see for example models in (Edelaar and Bolnick 2019)]. We envisage that the ancestor entity is the ‘building block’ for artificial life to evolve in BioVR and without it, the system does not have the evolving entity. The ancestor entity is equivalent to the ancestor species which gave origin to life on Earth, and is a common feature of artificial life systems [e.g., (Ray 1994)]. In other words, the ancestral entity is the first ‘living’ inhabitant of the virtual planet.

3. Gather a large empirical dataset of environment–traits–species interactions as a basic starting-point for determining how different species evolve in different ecosystems (e.g., evolutionary convergences, divergences, character displacement) – this could be called ‘rules of evolution’. This will allow the system to ‘know’ which adaptations are more likely to yield fitness advantages in a given environment. For instance, heat tolerance (or traits related to coping with high temperatures) is a likely to increase fitness of populations living in virtual habitats that resemble arid regions. The actual evolution of traits following the ‘rule of evolution’ will depend on the variability present in the ancestral entity populations and we envisage that, in a BioVR simulation, this parameter can adjustable according to the purpose or the needs of the virtual world.

One way in which evolutionary rules could be extracted from this dataset is using, for example, supervised learning and/or clustering algorithms (see Box 2) to extract general rules as to how species evolve (morphologically and behaviourally) across different environments, commonality between functional traits across species in the same environments, as well as the number, distribution, and behaviour of different species within the same environment. For instance, species living in warm habitats are likely
to share similar adaptations to high temperatures and thus, one could expect that virtual 
entities inhabiting warm virtual habitats should resemble follow similar patterns. Once 
these rules of evolution are estimated (or guessed) across all habitats of the virtual 
world, ancestral entities can evolve and differentiate accordingly.

4. Ideally, BioVRs are self-sustained, and thus it would be interesting to have the changes 
and adaptations in one time point to feedback into the system for the next time point. 
For example, imagine that a species evolves a remarkable adaptation to convert virtual 
resource A into B. This transformation should feedback into the system so as to allow 
new evolutionary rules, perhaps favouring other species to adapt and utilise virtual 
resource B (which is being produced) instead of virtual resource A (Fig 2).

5. Given this self-sustained cycle of interaction between entities and the environments, 
and the iterative system that modulates virtual evolutionary rules, BioVR can become 
an artificial ecosystem, fully accessible for exploration through VMR in inquiry-based 
learning quests. This allows students and researchers to experience and study evolution 
in this immersive environment, comparing the outcomes of evolutionary forces within 
different environments within a BioVR and across BioVRs with different setups. 
Furthermore, since data visualisation is key for understanding biological processes 
[e.g., (Karr and Brady 2000)] and is an essential component of affective learning, the 
use of VR to create BioVR worlds will allow VR to transcend the status of an 
educational tool that helps learning and teaching in Biology to become the main 
technology for experiencing and learning about virtual biological phenomena.

We provided these steps in order to quick-start ideas around the practical challenges necessary 
to realise the conceptual proposition made in this paper. We are not presumptuous of our 
knowledge boundaries and understand that experts may have better implementation methods 
and other tools that we are unaware. Having said that, these steps are aimed to foster open 
discussions that can generate international collaborations which may make possible for BioVR 
to reach the classroom as an effective educational tool of the future. It is important to mention 
that while the idea of BioVRs may seem now allusive, attempts to merge the fields of VMR, 
artificial life, and AI have been around for decades (Luck and Aylett 2000), with more recent 
efforts emerging from the astonishing ‘boost’ in computer power of our generation (Petrović 
2018; Zhang et al. 2018). We are also aware that virtual environments, AI and semi-
autonomous VMR agents have been developed for other purposes such as direct or assist users 
into tasks [see e.g., (Luck and Aylett 2000)]. To our knowledge, concepts similar to the one of
BioVR as presented in this paper have never been conceptualised let alone tested, which underscores the importance of opening this avenue of communication around the concept of BioVR for future developments that aid education of Biology. Future research and discussion should therefore aim at assessing the feasibility of the concepts proposed here.

**Fig 2 – Conceptual overview of the steps to build a BioVR.** A supervised machine learning algorithm is implemented to empirical environment-trait-species datasets in order to extract the patterns (or ‘rules’) of evolution across environments. Meanwhile, the initial settings for the BioVR world and the ancestral AI entity are also set. The settings include physical and environmental conditions, as well as patterns of lifespan, movement, and reproduction of the AI entity. Next, the ‘rules of evolution’ are incorporated into the BioVR and AI entity with original settings, and the BioVR is allowed to evolve. Note that the evolution patterns in the BioVR are then fed-back to the machine learning model, which is updated. This way, the only input from empirical data is at the initial states, and BioVR are allowed to evolve independently afterwards. As a result, we can measure and visualise species evolution as it happens, in an immersive experience of the BioVR.
Conclusion

The use of VMR has provided promising results for consolidating learning across secondary and tertiary biology education. With increasing technology, the combination of VMR with Machine Learning and AI has the potential to create a self-sustained evolving virtual world (BioVR) that allow us to uniquely explore how life as we know evolves and responds to extreme climatic conditions. Thus, the use of new technologies and innovative applications can provide better learning outcomes and student experiences in face-to-face, blended, and distance learning contexts by amalgamating biological principles in immersive classrooms.

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Conflict of interest

The authors have no conflict of interests to declare.

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In a highly influential paper, Milgram, Takemura, Utsumi, & Kishino (1995) proposed the reality-virtuality continuum (see Fig 3) to classify Virtual, Augmented, and Mixed reality technologies. On one side of the spectrum is the real world (reality) and, on the other side of the spectrum, the fully virtual world (virtuality) where Virtual Reality (VR) in its strict sense resides. In between the extremes, stands Augmented Reality (AR) – which relies mostly on real world elements but with the addition of virtual entities; the best known (and controversial) example of AR has been Pokemon Go! (Serino et al. 2016; Zsila et al. 2018) – and Augmented Virtuality (AV) with the opposite of AR, that is, mostly virtual world but with the addition of ‘real’ entities. AR and AV are cases of Mixed Reality (MR), where real and virtual elements are intertwined within the application (see Fig 3). For the purpose of this paper and for simplicity, we refer to AR, AV, and VR all as virtual and mixed reality (VMR) applications because they all have some degree of virtual components introduced into the application.

Fig 3 – The reality-virtuality continuum. AR – augmented reality; AV – augmented virtuality; VR – virtual reality (based on Milgram et al., 1995).
Box 2 – Supervised and unsupervised machine learning.

Machine learning models can be broadly classified into **supervised** or **unsupervised** learning algorithms, depending on the structure of the data (Mitchell, Michalski, and Carbonell 2013) (Note: there are intermediate cases called *semi-supervised learning* which we will not consider here, see e.g., (Zhu and Goldberg 2009) for details). Unsupervised learning algorithms use data in which the outcome is not yet labelled or identified, and therefore the algorithm cannot ‘know’ the outcomes in advance. The algorithm then learns how to classify and predict the outcome from new observations based on the inherent structure of the data at hand. An example of unsupervised learning is the clustering of groups within a dataset (Fig 4a). Conversely, supervised learning algorithms uses data in which the outcome is known, and the algorithm learns how to predict the outcome of future observations based on what was learnt from the information and outcomes obtained from previous data. An example of supervised learning is the classification (or prediction, in the case of regression models) of a new observation between two categories based on \( n \) number of characteristics or variables (Fig 4b).

![Supervised and unsupervised machine learning](image)

**Fig 4**– **Supervised and unsupervised machine learning.** a) Schematic representation of an unsupervised learning model. Unlabelled data is used in unsupervised learning algorithms for
clustering. b) Schematic representation of a supervised learning model. Labelled data are used in supervised learning algorithms for classification.