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Augmented Reality for Personalized Learning Technique: *Climbing Gym* Case Study

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Abstract

Augmented Reality is a technology that allows to expand the traditional learning techniques complementing the perception and interaction with the real world that allows the student to be in real environment with additional information generated by the computational algorithm. However, the knowledge and applicability of this technology in the field of personalized education is not a common practice. In this article, personalized education strategies are applied in the process of developing the application for indoor climbing teaching techniques. The application allows the trainer or climber to select the climbing holds that make up a route and display it by visualization on a projector to customize the training program. The system has the detection algorithm and recognition of climbing holds in real time and visualization of the route to climb. This kind of applications using emergent technologies oriented to personalized training has enormous potential for efficient education.

Keywords: personalized learning strategies, augmented reality, Kinect, educational applications, climbing.

1. Introduction

Nowadays, the use of IT for the creation of immersive environments for learning of specific topics has been implemented in wide variety of disciplines. On the edge of technological advances, the education sector is going through a renovation in which technology is used as a tool, adding a value to a learning process and shared knowledge. Through IT, communication spaces can be established that adopt a new modality of relating to the object of study and, in addition, allow the transmission of comprehensive knowledge between the student, the facilitator and the environment.

Education through virtual environments is more focused on the needs and pace of student learning. Therefore, virtual education promotes connections not only with technology but also between the facilitator, the student and behavior, thus, allowing greater interconnectivity with the world and with the sources of information, promoting collaborative learning. The virtual education perspective includes certain categories that are appropriated in a very specific way, according to the learning criteria that are worked on (Chen & Yang, 2014).

On a technological level, virtual environments are based on a human-computer interaction, where the user interacts with the elements of the system and the server makes the connection with the environment possible. The application of virtual environments has great

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potential in education, more specifically when talking about contexts where learning is immersive or exploratory (Zamora-Musa, 2016).

- It is presented the conceptual framework of personalized learning as an educational approach and the principles of adaptive educational systems.
- It has been proved that it is possible to implement personalized training program through emerging technologies as an augmented reality.
- It has been developed meaningful learning framework of the physical education in specific for rock climbers using an application with augmented reality.
- The application recognizes the movements of the human body, as well as its interaction with virtual objects using the 3D sensors.

Recently, there has been proposed many solutions that make use of human-computer interaction technologies applied to real-world sports, such as trampoline, climbing and mixed martial arts, among others (Kajastila & Hämäläinen, 2015). As for the sport of climbing, there are a number of projects and research that are intended to support the process of training, for example *Strange Beta* (Phillips, Becker & Bradley, 2012). They use a mathematical model and machine learning for the design of indoor climbing routes. It is an assistant that manages to configure climbing routes through machine learning, that involved analyzing climbers to be able to describe their movements by following their routes, so that system could learn the patterns. Due to the nature of this system, it is designed for experienced climbers and expert trainers. The use of *Strange Beta* consists of defining one or more routes, using a computer-readable descriptive language of climbing routes.

Other proposal consists in automatic detection and classification system of climbing activities based on inertial measurement units (IMUs), that are placed on the wrists and feet of the climber and can record limb acceleration and angular velocity (Boulanger, Seifert, Herault & Coeurjolly, 2016). This project is focused on the regularization of the climber's posture, the free movement of his limbs by following different routes. They based on the behavior of climbers when they are kept in a static due to fatigue, especially the expert climbers as an example they refer to the fact that they tend to try at least three climbing holds before to choose the ideal. That is why its objective is to detect and quantify some common climbing activities: immobility, postural regulation, hold exploration, etc. As a result, there was designed a system that requires manual corrections to obtain knowledge of the progress, and based on this, a statistical model is constructed for the norms of acceleration and angular velocity.

Another project known as *ClimbSense* is an automatic recognition system of climbing routes using IMU on the wrists by extracting the characteristics of a registered climbing, like the previous proposal, and using them as training data for the recognition system. Consequently, this research is also focused on optimized route tracking, through a system that automatically records and recognizes the route that a user climbed during a climbing session. The climber is tracked by IMUs. The characteristics that are extracted from the collected data are used as training data for the recognition system (Kosmalla, Daiber & Krüger, 2015).

It should be said that today there are interactive climbing walls that have mostly focused on the use of sensors and lights. A new climbing wall enhanced with hardware and software makes a combination of computer games with sports climbing (Liljedahl, Lindberg & Berg, 2005). Each wall has a printed circuit board (PCB) incorporated with a capacitive sensor and LEDs that transmit sounds and music to convey a better gaming experience.

One of the first projects mentioned in the literature with some similarity to the present work, is the one presented by Daiber, shows a system that provides an intuitive way to create and share routes. In the research paper it is presented a mobile application of augmented reality *BouldArt* for the adjustment of several parameters in climbing training (Daiber, Kosmalla & Krüger, 2013). This approach supports cooperative training and uses synthetically generated images of climbing walls that are then used as traces for existing real walls. In order to establish the automated system, they needed to take photographs of a large number of *holds*, then trimmed and stored them in a database. Subsequently, an image of the wall is created by aligning the visualized *holds* on a predefined grid with the dimensions of the real ones.

As it has been shown previously a market focused in novel products has been extended, offering a technological experience in a real and virtual environment. For example, games that are focused on the practice of real-life sports. In these games, new technologies of digital image processing and computational vision are integrated for their learning and training, so they are quickly becoming a new category for users that enjoy new experiences of sports games with human-computer interaction (Kim, 2017). The approach that distinguishes this work consists of combining the principles of personalized education and its subsequent application to accelerate the acquisition of skills and abilities that convert climbing training to an efficient process that adapts to the needs of the climber. In our project, we are developing a new augmented reality climbing wall, where will use a combination of the wall analysis, projected graphics on an artificial climbing wall and body tracking through artificial vision.

2. Methodology

A lot of discussions are dedicated to the radical change of the learning process and almost all the parameters involved in learning: where do we learn, when, how, with whom and from whom, of course what and especially for what we learn (Collins, Halverson, 2010). Today, technology is advancing rapidly, providing benefits to the users and demanding changes in the traditional educational process where the teacher or coach was the only carrier of exclusive information that he shared. Traditional education system, which was built to standardize the way of teaching falls for the simple reason that if two students are learning the same subject, it does not mean they learn at the same pace or should follow the same pathway. Each person has different learning needs at different times to process the information.

Modern society requires implementing new effective learning methods paying attention on the process, because what is learned is as important as the way how it is learned. It is about guiding the learning process – how to learn – to develop the skills of learning for oneself "learn to learn" and "learn to think". In the constructivist model, the teacher is a mediator of learning in two senses: first, guiding and structuring learning according to the student needs and, secondly, building and offering a meaningful material or creating a meaningful content.

The growing importance of constant actualization of the professional skills and continuous improvement is a reality that people face during all their lives. One way of access to knowledge in the information society is the individual learning path. Last years the opportunities, resources and instruments for learning are diversified and cease to be associated exclusively or as a priority to a single context of activity usually in the context of formal education, the focus of interest shifts to the learning experiences and the learning process that take place in the different contexts of activity through that people are passing (Arnseth & Silseth, 2013).

2.1 Towards a personalized learning process

Learning styles are cognitive, affective and physiological traits that serve as relatively stable indicators of how students perceive interactions and respond to their learning environments (Keefe, 1988). Cognitive traits have to do with the way students structure content, form and use concepts, interpret information, solve problems, select means of representation: visual, auditory, kinesthetic, etc. Affective traits are linked to the motivations and expectations that influence learning, while physiological traits are related to the student's biotype and biorhythm. The learning style is the way in which a learner begins to concentrate on new and difficult information, treats and retains it.

The following attributes describe essential parts of personalized learning model (Benson, 2013):

Flexible learning environment: Multiple instructional delivery approaches that continuously optimize available resources in support of student learning. Instructional materials allow students in different ways and pace resolve practical tasks.

Learner profiles: Analyze abilities of each participant and capture individual skills, gaps, strengths, weaknesses, interests and aspirations.

Personal learning paths: Each student has learning goals and objectives. Learning experiences are diverse and matched to the individual needs of students. They should have frequent opportunities to reflect on what they are learning, apply knowledge in authentic and relevant contexts and about their success in learning.

Individual mastery: Instructions that are aligned to specific student needs and learning goals. Also continuously assesses student progress against clearly defined standards and goals. Students advance is based on demonstrated mastery and targeted instructions.

So, each person develops and enhances a certain strategy to reach the meaningful knowledge. Someone learns from reading, others from practicing or group work, others from individual isolated work, however all students have different traits of different learning styles in different percentages and we are considering these different styles of learning while planning the application.

2.2 Meaningful learning

The important factor for meaningful learning is prior knowledge, prior experience or prior perception, and also student must express a willingness to non-arbitrarily relate the new knowledge to its cognitive structure (prior knowledge). In addition, in order to achieve meaningful learning, the material or content should be potentially significant, that means it can be substantially related to some specific cognitive structure of the student that must have logical meaning. This meaning refers to the inherent characteristics and the nature of the material or content to relate it intentionally and substantially to the corresponding and relevant ideas that are available in the student's cognitive structure.

When the potential meaning becomes new, differentiated and idiosyncratic cognitive content within a particular individual as a result of meaningful learning, it can be said that it has acquired a psychological meaning in this way the emergence of the psychological meaning does not only depend on the representation that the student makes the material logically significant, but also that such student actually possesses the necessary ideational background in his cognitive structure (Ausubel, 1983). The fact that the psychological meaning is individual does not exclude the possibility that there are meanings that are shared by different individuals, these meanings of concepts and propositions of different individuals are homogeneous enough to enable communication and understanding between people.

When the student shows a disposition to relate in a substantive and non-literal way the new knowledge with their cognitive structure means their disposition for meaningful learning. Thus, regardless of the potential meaning of the material to be learned, if the student intends to memorize arbitrarily and literally, both the learning process and its results will be mechanical. In case the material is not potentially significant and if it is not related to its cognitive structure regardless of the meaning of the student's disposition, neither the process nor the result will be significant.

The facilitation of meaningful learning according to Ausubel is the deliberate manipulation of relevant attributes of the cognitive structure for pedagogical purposes. It can be implemented in two ways (Ausubel, 1983): substantially and programmatically.

Substantially for organizational and integrative purposes means by using the unifying concepts and propositions of the content of the learning subject that have greater explanatory power, inclusiveness, generality and relationality of this content.

Programmatically means by using programmatic principles to sequentially order the subject of learning, respecting its internal organization and logic and planning the implementation of practical activities.

In substantive terms, Ausubel postulate that to facilitate meaningful learning it is necessary to pay attention to the content and cognitive structure, trying to *manipulate* the both (Ausubel, 1983). It is necessary to make a conceptual analysis of the content to identify concepts, ideas, basic procedures and concentrate on them the instructional effort. It is important not to overload the student with unnecessary information, making cognitive organization difficult. It is necessary to look for the best way to explicitly relate the most important aspects of the content of the specific subject with its own relevant aspects of the cognitive structure of the learner.

This relationship is essential for meaningful learning. In summary, a prior analysis of what is going to be taught is essential. Many times, the order in which the main concepts and ideas appear in educational materials and programs is not the most appropriate to facilitate interaction with the student's prior knowledge.

The critical analysis of the teaching subject must be done thinking about the student. In the case of climbing discipline, we will develop the program that will record the mistakes made by the climber. These mistakes then will be analyzed by the trainer along with the climber and this moment is suitable to provide meaningful learning based on previous experience.

2.3 Augmented reality in educational process

Thanks to technological advances, there are many innovative solutions in different areas, such as technologies and interfaces for immersive environments.

Augmented reality (AR) in education supplements reality rather than replacing it like Virtual reality (VR) with digital information designed to be entertaining and relevant to the activity learners are engaging. Augmented reality will provide an understandable and positive experience of the surrounding world only if the real and virtual scenarios will be synchronized in space and by context. AR technology renders content generated by computer on users' physical surroundings. Klopfer (2008) in his book characterizes AR in terms of the amount of digital media that is provided to the learner, ranging from lightly augmented reality where information is provided primarily through the real-world environment, to heavily augmented reality where most of the information is provided virtually by device.

The architecture of any AR system is based on two critical elements: tracking and visualization. The degree of immersion and integration in mixed reality depends on them. The tracking system determines the exact position and orientation of real and virtual objects in the real world. The graphic system, or visualization, in addition to generating the virtual objects, combines all the elements of the scene, real and virtual, showing them on the screen. Correct and effective visualization of these data using an AR technology can reduce the misunderstanding/

misinterpretation in spatial and logical aspects. There are varios significant applications of AR in education (Reinoso, 2012):

(1) Learning based on discovery.

(2) Development of professional skills. Vocational training is one of the main areas of application of the AR allowing to improve understanding in practical training activities and recreate real work situations.

(3) Books and learning materials with AR.

(4) Educational games with AR (include Games based on markers and codes, in which 3D elements are interacting; Games based on gestural recognition, in which the user is part of the game interface; Games based on geolocation, they are played in a social and collaborative way, and where the physical space becomes the game scenario).

(5) Modeling 3D objects. Using object modeling tools and AR applications, the student can create and visualize 3D models and manipulate them: zoom them in, zoom out, rotate them, place them in specific places or explore their physical properties.

In the quantitative study of Redondo (Redondo, Fonseca, Sánchez & Navarro, 2014) on the advantages obtained with the use of applications with AR in the educational process it is mentioned that improvements were reflected both in the degree of motivation shown by the students and in the final qualifications. So, Augmented Reality that provides new environments to explore, new challenges and new ways of teaching could be adapted to different learning abilities.

Explanations of differences in the ways that people learn are not focus only on cognitive factors having to do with the path to receive information and process it, such as learning styles. Several areas of research point towards the important effect of positive emotions on successful personalized learning. In this context AR reinforces learning and increases motivation to learn.

This investigation supports better design because it addresses for a more comprehensive set of psychological factors such as immersive experience by using AR reality to reach high level of enjoyment.

3. Case study: Development of the training solution for the Climbing gym

Nowadays there is a great variety of sports games that make use of new technologies. In relation to the rock climbing, there are ones played on screen, which consist of showing a virtual game projected on artificial climbing walls. These games use Microsoft's native technology – Kinect. However, such games are usually expensive and hardly personalized, since most of the companies that offer this type of products are international, specifically dedicated to the development of interactive games offering a complete equipment for their installation. On the contrary, the present work has an aim to cover needs of the local schools of climbing implementing the principles of personalized teaching and to develop an algorithm that includes procedures for the digital processing of images with computer vision methods for the detection and analysis of *climbing holds*. That will help to develop a route projection system on climbing skills. The focus groups to which this application is directed are mainly beginners. However, at any given time the application can be modified for any installation and climbers' level, encouraging the practice of climbing.

3.1 Recognition of climbing holds on climbing walls in real time

The design process involves following next key stages:

• Acquisition of images

To acquire images correctly, it is necessary to evaluate different factors that directly affect the capture process, the hardware and software that are involved, as well as the environment and the positioning of the elements (lighting, climbing wall, position of the camera, etc.) The Kinect ONE v2 RGB video camera was used to acquire the scenes in real time, with a resolution of 1920x1080 at 30 fps. Another point is the programming language and the characteristics of the device for processing. For the development of the algorithm, the C ++ programming language was used together with OpenCV, an open source library to develop artificial vision applications and for mobile development the Android Studio programming was used. As for computational requirements for processing, there were considered such important aspects as the processor, hard disk, RAM and video card.

Finally, the elements that define the environment and the way of placing them were identified: a concept of the experimental environment consists of a climbing wall, a multimedia projector, the Kinect camera and a computer.

• Image preprocessing

A start point of any image processing is enhancement. Image enhancement is the procedure of improving the quality and the information content of original data before processing. In our case it consists in eliminating the noise produced by the camera, change the exposure - effects of the lighting that altering the images. It will make possible highlight the important aspects that we need to analyze. The Gaussian filter (one of the best-known filters for noise elimination) is based on the mathematical operation of the convolution. It consists of the sum of the convolution of each point of the input matrix with a Gaussian kernel, by traveling pixel by pixel of an image, with a mask or kernel of NxN size. The Gaussian filter is defined as follows:

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
(1)

Then for the enhancement of the *climbing holds* it was applied subtraction or restoration of the images, a common arithmetic operation in computational vision. Background subtraction is widely used for object detection, which is the difference between a current pixel and a reference pixel, in our case the background image. The climbing wall does not vary much with time, that is, the camera will be statically focused on it as the wall only changes when new *climbing holds* are placed, and in this moment the detection procedure is performed. The areas where the difference is significant will indicate the location of a new object. Background subtraction attempts to eliminate variations in color levels, first approaching them analytically with a background image f_b and then subtracting this approximation from the original image. So, the new image f_n is:

$$f_n(x) = f(x) - f_b(x)$$
 (2)

• Segmentation, Recognition and classification

Image segmentation is the process of partitioning a digital image into different segments and discrete regions. Image segmentation is typically used to locate objects and boundaries in images and there are a wide variety of techniques that leads us to the conditions of the problem to be solved. Image segmentation is the partition of an image f(x, y) into a set of non-overlapping, homogeneous regions with respect to some criteria common for the entire image. The objective of segmentation is to separate the objects of interest from the non-relevant rest considered as background. To achieve the segmentation of the *climbing holds*, the resulting image was subtracted from the background in the RGB color space. Then it was transformed into the

HSV color space. The HSV model is obtained by deforming the representative RGB cube to inverted hexagonal pyramid. To threshold the image, a certain range is taken, in this case the largest range that characterizes the black color in the HSV model, that is the background color has obtained from the background subtraction. So, the following step used to create an inverted binary mask to obtain the objects:

$$f_{thres}(x, y) = inrange(f_{HSV}(x, y), min, max)$$
(3)

fmask(x,y)=if fthres(x,y)>T fthres(x,y)=0, if not fthres(x,y)=255 (4)

In the next step we found the contours of the segmented image. The contours are curves that join the continuous points of an object that has the same color or color intensities. They help us to analyze the shapes and therefore detecting and recognizing the objects. Finding outlines in a binary image is much simpler, since the objects are whites and the background is black. For the search and drawing of the contours, OpenCV has the functions **findContours ()** and **drawContours ()**. The first function recovers contours of a binary image using the algorithm of Satoshi Suzuki (Suzuki, S. and others 1985), that is based on the fundamental technique in the processing of binary images – *Border following*.

void cv::findContours(InputOutputArray image,OutputArrayOfArrays contours,OutputArray hierarchy,int mode,int method Point offset = Point())

where: **image** is the binary input image of a single 8-bit channel; **contours** is an array of dot vector where the detected contours are stored; **hierarchy** is an optional output vector that stores information about the image topology; **mode** is mode in which the algorithm retrieves (contours, for example); **RETR_EXTERNAL** retrieves only extreme outer contours; **method** is contour approach method, for example; CHAIN_APPROX_NONE store all contour points.

We used **drawContours()** for the drawing of the contours. Its first argument is the original image, the second argument is the arrangement of contours, the third parameter is the index of contours for drawing individual contours, and the remaining arguments are optional such as color, thickness, etc.

void cv::drawContours (*InputOutputArray image,InputArrayOfArrays contours,int contourIdx*, *const Scalar&color,int thickness=1*,

int lineType = LINE_8, InputArray hierarchy = noArray(), int maxLevel =
INT_MAX,Point offset = Point())

• Mobile application development

The *Canvas* class of Android represents a type of canvas or surface where you can draw lines, circles, text, etc., through a variety of methods that it provides. For the creation of the mobile application that shows the detected *climbing holds*, an HTTP connection was made from Android to a web server, so each time the objects were detected, they were sent to the server and stored in a *.txt* file for later use. In our case they are drawn in the mobile application. The general functionality of the application is following:

(1) By monitoring the changes in the climbing wall, the server is notified every time a new climbing hold detection is made. In turn, the server sends a notification to the cellphone through the application.

(2) Upon receiving the notification, the mobile application makes a connection to the server to obtain the updated detected objects.

(3) These objects are drawn and represented as contours.

(4) The route is defined by selecting the *climbing holds* in the applications.

• Testing process

To offer better results, it was necessary to have a controlled environment, since natural environment has unpredictable starting conditions. We have used a frontal lighting, where the light directly affects the object, so it allows to distinguish details of the objects, as well as their shape. The following prototype was tested on the wall located in Irapuato, *MundoBloke*:

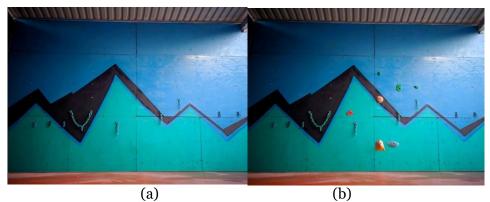


Figure 1. Climbing wall: (a) Wall without holds, (b) Wall with holds

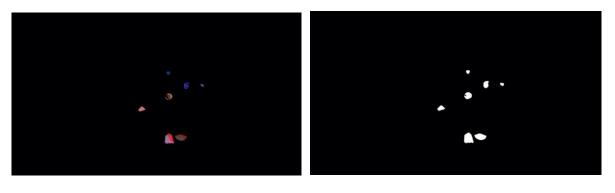




Figure 2. Processing: (a) Background subtraction, (b) Segmented image



Figure 3. Detection of climbing holds

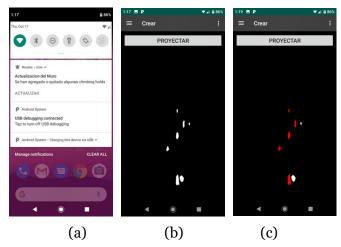


Figure 4. Mobile application: (a) reception of the notification, (b) visualization of the detected climbing holds, (c) selection of the climbing holds

3.2 Interaction of the human body with virtual objects using 3D sensors

The next stage of the project includes interaction of the climber with the route created. The computer system was developed in the programming environment of Microsoft Visual Studio 2017, using C ++ as the programming language as well as the software development kit (Software Development Kit), Kinect for Windows SDK 2.0, the NtKinect library (Nitta and Murayama, 2018) and the open source library for OpenCV computer vision.

Figure 5 shows the general procedure for the recognition of the movements of the human body and its interaction with virtual objects that are visualized in real time.

- User

Kinect 2 for Windows can monitor up to six people simultaneously within its field of vision and can detect 25 joints for each of them. People can be detected while standing or sitting. The optimal distance to detect the human body by means of Kinect is 0.5m to 4.5m, and it has a horizontal viewing angle of 70 ° and vertical of 60 °.

To interact with the system the user must be positioned in front of the Kinect device, either standing or sitting at the distance mentioned above.

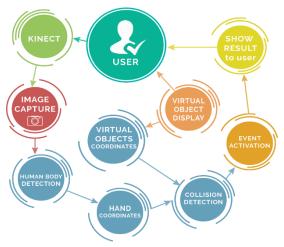


Figure 5. General process of the interaction of the human body with virtual objects.

- Kinect

Kinect is a motion detection device created by Microsoft for Xbox console games and Windows personal computers. The versatility of Kinect allows you to see the movements of a complete human body, as well as detect small hand gestures.

The Kinect sensor provides color image frames from its RGB camera. It also has an infrared emitter that, together with a depth sensor, can measure the depth of the captured images at a millimeter resolution. It has a four-microphone array that transfers audio data to the SDK development kit.

- Image capture

The Kinect RGB camera can acquire images with a resolution of 1920x1080. Because the OpenCV library uses the BGR or BGRA format by default, it has been decided to use the NtKinect library that has functions that convert BGRA to RGB format automatically without the need for the programmer to develop additional code. NtKinect uses the *setRGB* () function to obtain the RGB image from the Kinect camera and handles it using the *rgbImage* variable.

- Human body detection

As mentioned above, the depth sensor can detect up to 6 people simultaneously with 25 joints of the each one when they stand and 10 joints when they sit at a distance of 0.5m to 4.5m.

To detect a human body, it is first necessary to obtain the position of the joints using a structure type variable used by Kinect for Windows SDK v2.0 called "Joint", and has the following member variables:

- Joint_Type: Type of articulation.
- Position: 3D coordinates that represent the position of the joint.
- TrackingState: Value used to indicate the tracking status of the joint.

Using the NtKinect library, you can access the joint information using the *setSkeleton* () function.

- Obtaining the coordinates of the hands

To obtain the coordinates of the hands it is necessary to take into account that Kinect v2.0 has 3 coordinate systems, namely ColorSpace, DepthSpace and CameraSpace. When using information obtained from different Kinect sensors at the same time, it is necessary to convert the coordinates to match. For instance, the CameraSpace coordinate system uses a 3D coordinate system (x, y, z), and the ColorSpace system uses a 2D (x, y) system. In this case a coordinate mapping is made. This is made using the Kinect for Windows SDK v2.0 ICoordinateMapper class, which will convert a 3D coordinate system to another in 2D.

Hand positions are obtained from the joint type (*JointType*) for the articulations (*Joint*) *JointType_HandLeft* for the left hand and *JointType_HandRight* for the right hand. The coordinate system of the hands is CameraSpace and it is necessary to map them to the ColorSpace system to obtain their coordinates in X, Y, and thus obtain their corresponding position in the RGB format image.

- Virtual object display

Using OpenCV virtual objects are displayed at the monitor. Each object is drawn as a circle. In this project, we used the *cv::circle ()* function of OpenCV library.

- Obtaining the coordinates of virtual objects

One of the input parameters for drawing the circles with the *cv::circle* () function is an X, Y coordinate point on the screen where the circle is displayed. Each of the X, Y coordinates of the center points of the circles are stored in an array or vector in order to have their positions stored.

- Collision detection

A collision is the interaction or clash between two or more bodies where at least one of them is in motion. Therefore, to detect the interaction of the hands with the virtual objects it is necessary to track the hands and obtain their positions in each moment to compare their coordinates with those of the circles. However, until now the coordinates of the center point of the circles are still and the collision must be detected from the moment there is contact with its circumference. Therefore, it is important to consider the radius of the circles when comparing the coordinates.

- Event Activation

In this phase it is defined what happens after a collision has been detected between the user's hand and a virtual object; an event or action that has been given to the user is to be able to move the virtual object that is displayed on the screen when wielding the hand over the object, also when positioning the hand on the object it will change color.

- Show result to user

The result of the collision is visualized by changing circles color to green, which indicates that the user has put his hand on a virtual object, also when closing or wielding the hand, the circle will change its position and coordinates X, Y to move together with the hand when moving it, if the user opens the hand the circle will stop moving.

- Summary of Results

In this project a basic computer system was developed to interact with virtual objects that are displayed on a computer screen. It was found that Kinect tends to present certain inaccuracies if you do not have the appropriate distance, position and lighting when facing this device, which causes false positives to occur when another part of the body touches a virtual object and is taken as valid, although it has not been touched with the hands. To try to solve this situation a timer was applied when having contact with a virtual object, therefore, it is necessary to maintain the position of the hand on the object for a second so that it can be considered as a valid interaction or collision, in this way the incidence of false positives has been significantly reduced.

3.3 Results

The project is composed of the hardware-software solution for customizing the training in rock climbing. The wall and the *climbing holds* positions analysis is based on the computer vision analysis of the image acquired by the Kinect2 camera using the OpenCV library. After the analysis, the climbing holds are being classified and appear in their corresponding positions in the Android application. Using the application, the trainer selects the route which is illuminated by means of mapping with a multimedia projector. The route correctness is controlled by recognizing the movements using the 3D sensor of the Kinect2. Basing on the result of the series of routes, the trainer gets the statistics of the errors and may individualize the training methods by modifying the complexity of the routes, number of repetitions and required speed.

4. Conclusions

Analyzing current trends in education, we confirm that recent years have shown that the way of communicating knowledge is changing with the advancement of technologies. Virtual education has a strong connection with immersive environments. Debates about the future of education center on changing the process of learning, to embrace technology in the classroom the student obtain meaningful skills thanks to efficient human-machine interaction and develops new potential.

In our project we implement the principles of meaningful and situated learning. We also facilitate the communication of the trainer and climber through immersive experience. The project in its current state has several disadvantages such as artificial illumination requirements for precision climbing holds recognitions, uncertainty in the holds classifications as well as manual training programs definitions. However, future development including advanced clustering algorithms, neural networks and self-learning training algorithm would allow to overcome these problems and create fully-functional climbing training product.

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Enhancing Exploratory Learning Using Computer Simulation in an E-learning Environment: A Literature Review

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Abstract

Computer simulation has been shown to elicit exploratory behavior and creativity in learners. Various researches have indicated that during an exploratory learning process students can acquire knowledge either through inquiring or exploring an open learning environment. Further, the research shows that as opposed to instruction-based learning, exploratory learning is mainly based on self-motivation by learners. Therefore, computer simulation when used to enhance exploratory learning concept especially in an e-learning platform, has been seen to achieve the learning objectives as explained by Bloom taxonomy. In this regard, computer simulation has been seen to help learners conceptualize important concepts especially in science subjects. Additionally, the use of simulation is regarded as an aid to improving understanding of various concepts as well, as helping increase breadth of knowledge.

Keywords: exploratory learning, computer simulation, e-learning environment.

1. Introduction

Prevalent learning theories have shown that the learner is no longer viewed as an "empty vessel," but rather as an actor who is actively involved in constructing and reconstructing of knowledge base (Metsärinne & Kallio, 2007). As such, this point of view is apparent in modern studies that have shown the importance of the active role a learner plays in the learning process and the importance of the foreknowledge. In view of this, various types computer assisted instruction exist that support this type of learning approach. Such an example is the use of computer simulation that has been seen to elicit exploratory behavior in learners (Salleh, Tasir & Shukor, 2012). It has been shown that during exploratory learning, students are able to acquire knowledge through either inquiring or exploring in an open learning environment. Further, students are able to explore a certain domain by self-motivation rather than being instructed. According to various researches, all approaches to exploratory learning are based on four principles; learners can and should control their learning, knowledge is multidimensional, learners approach to tasks are diverse and it is possible for learning to feel natural (Iqbal, 2012; Metsärinne & Kallio, 2007; Njoo & De Jong, 1993). In addition, different tools are used to enhance exploratory learning that includes microworlds, hypertext and games & simulations, but this study will focus on simulation as implemented in e-learning systems.

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2. Methodology

We limited this systematic literature review to the use of computer simulation in exploratory learning and its application in e-learning platforms.

2.1 Research questions

(1) How does computer simulation affect students understanding of concepts in an elearning environment?

(2) Does computer simulation increase breadth and depth of knowledge for a learner in an e-learning environment?

(3) How does use of computer simulation affect student's conceptualization capability in an e-learning environment?

2.2 Data sources

This review sourced its data from four electronic databases: Google Scholar, Springer, IEEE, and Science Direct.

The researchers conducted databases search and received 535 results, but only included the first 200 most relevant results. The search for the most relevant articles was conducted using well-defined query criteria as shown below. (Computer simulation OR "simulation") AND (Exploratory learning OR e-learning OR "e learning" OR exploratory e-learning).

The search was conducted in October 2018, and the researchers made the search base as broad as possible in order to get as much results as possible that would try to answer our research questions. The Figure 1 is a summary of the query criteria and the search results.

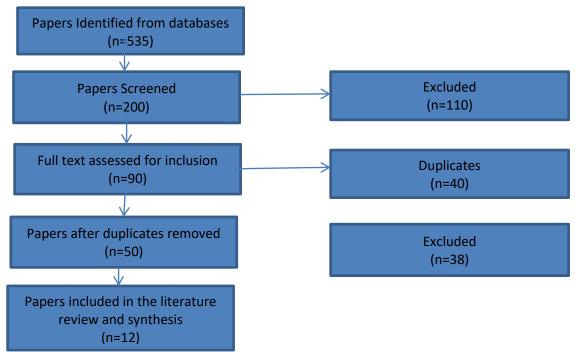


Figure 1. Summary of the query criteria

3. Learning objectives and Bloom taxonomy

The value and importance of computer simulation in higher education cannot be overlooked especially its relationship with learning objectives. The general and core objective of learning describes skills and knowledge students need to gain, and they are always core to the design and validation of any educational system (Miller, Nentl & Zietlow, 2014). Various frameworks like Bloom's taxonomy have been used extensively to explain learning objectives (Ekren & Keskin, 2017). According to various studies, simulation has been framed as a technology that engage students in deep learning (Ekren & Keskin, 2017; Miller et al., 2014). As such, skills like critical thinking and problem solving are central to achieving learning objectives. According to Bloom Taxonomy, learning objectives could be classified into three domains. Cognitive domain looks at the skills that regard knowledge, comprehension and critical thinking in regard to a particular subject. On the other hand, affective domain describes skills that make people react emotionally and thus it happens the behavioural level. Lastly, psychomotor domain looks at the application of the learning in solving problems (Ekren & Keskin, 2017). With the emergent of technology and its integration with education, there was need for the Bloom taxonomy to be revised so as to cater for different generations of learners as well as modes of learning like elearning. As shown by the revised Bloom taxonomy, the classification system was designed to help instructors clearly define learning objectives. As such, designers of e-learning systems need to realize that writing clear and precise objectives of learning is essential to the success of the students (Ekren & Keskin, 2017; Miller et al., 2014). In view of this, the revised Bloom Taxonomy is vital in defining e-learning objectives, as well as the associated behaviour of the learner, which is influenced to meet the learning objectives.

According to Bloom, one of the levels of the model is knowledge (Ekren & Keskin, 2017). Research has shown that this level is the easiest to implement in the e-learning environment. Through an e-learning platform, and especially that utilizes simulation, it is easy to impart knowledge in form of facts, terms and basic concepts. The other level is the comprehension, which refers to the ability to understand something. The idea behind this element is to ensure that the learners have received the information provided in the e-learning course and can understand advanced concepts and techniques. Another level in the model is application, which refers to the ability of the learner to interact with the e-learning system through exercises and simulations with the endeavour of applying the acquired knowledge. This stage requires designers of the system to focus on using real life situations that are familiar to learners. The learners can then apply the learnt facts, knowledge and rules to solve problems. At the analysis level, the learner has developed an understanding of the subject and can analyse problems and gather the correct information that helps in making decisions. At the evaluation level, the learner has become an expert and can be trusted to make recommendations based on analysis of a situation. The final level in this taxonomy is the creation step that requires learners to come up with original work based on the concepts learned. Being the highest level of the Bloom taxonomy, learners come up with their own work as a way of demonstrating that they have mastered the subject (Ekren & Keskin, 2017; Miller et al., 2014). This shows that a designer of an e-learning system must follow the cognitive domain of Bloom taxonomy so as to come up with a system that ensures learning objectives are met.

4. Review of past literature

4.1 Definition of concepts

Teaching science concepts requires a proper approach that will facilitate conceptualization of important ideas. Consequently, a computer simulation will provide a model for teaching events, objects and phenomenon (Metsärinne & Kallio, 2007). This are applied in teaching to model concepts that are difficult to observe in a classroom environment. A computer-based simulation allows students an opportunity to interact with a computer representation

through a model of a physical world or using a theoretical system (Tawil & Dahlan, 2017). Therefore, a computer simulation creates a learner centered classroom environment that enables students to explore systems, use variables and examine hypotheses.

Enhancing exploratory learning is a major problem in conventional classrooms. A computer simulation program can effectively be utilized by a teacher as a demonstration so that students can explore several phenomena that would be difficult to understand in a conventional classroom. Secondly, computer simulations enable learners to experience a realistic understanding that facilitates manipulation of knowledge. As such, students benefit from achieving a better understanding of concepts under investigation. For instance, animations can be combined with visualizations to improve insight development of a complex physical phenomenon (Yas, Ahmed & Tala, 2014).

4.2 Developing content and processing skills

Studies on impact of computer simulations in promoting exploratory learning have demonstrated a positive finding. Researchers have observed that computer simulations can enhance exploratory learning through developing content, processing skills, encouraging complicated goals and facilitating a conceptual change. Basically, majority of studies have shown an increase in achievement for science skills through using computer-based simulation in learning and teaching (Thong, Lin, Siong & Lin, 2008). For example, simulations can replace learning or teaching where equipment is not available and cannot be set up (de Smale, Overmans, Jeuring & van de Grint, 2016). Also, it is an important teaching tool for performing experiments that are ordinarily impossible to undertake. This is because variables can easily be altered in simulations to promote learning prompted by questions from students, which is impossible to achieve using a real equipment. Here, computer simulations allow students to practice laboratory techniques prior to engaging in lab experience with actual equipment.

Studies on comparison of computer simulations and traditional classroom learning have demonstrated that the former can enhance exploratory experience. Learners become a valuable add-on in a traditional classroom because they act as pre-laboratory experiments. For example, (Salleh et al., 2012), it has been proved that computer simulations enhance learning of optical lenses. In a conventional classroom, textbooks offer a two-dimensional representation of concepts which is improved to three dimensional through simulations. For example, visualization created by computer simulations enhances mental constructs that facilitates critical thinking to describe and explain objectives. According to Njoo and De Jong (1993), computer simulations in a dissection lab makes it possible to identify correct and wrong answers through improving the skills for what-if and possibilities. Utilization of computer simulations enhances positive understanding of concepts and gaining of new skills. This enables students to improve their general understanding of complex science concepts.

4.3 Improving understanding

Enhancing exploratory concepts require computer simulations to make understanding easier. According to Tawil and Dahlan (2017) it has been postulated that structures are an easy way of understanding a complex system like DNA and RNA enables students to understand their functions. Here, simulations are important so that they can organize small pieces of information to become large so that it can reduce the amount of memorization that would be required to achieve a better way of determining a logical relationship of underlying ideas (Tawil & Dahlan, 2017; Metsärinne & Kallio, 2007). Computer simulations provide learners with an opportunity to view and interact with models representing a particular phenomenon and processes.

Thong et al. (2008) have revealed that computer simulations enhance student understanding through attaching mental images. Similarly, other researchers had earlier identified that a mental model is a required level of understanding and interpretation of an existing concept that is influenced by experiences, beliefs, history and personal opinion (Miller et al., 2014). Mental models should be generated by students to enhance understanding of new concepts. As such, teachers rely on models as a basis on enhancing learners' ability of generating individual models through computer simulations.

Exploratory learning requires understanding of scientific concepts in the context of a daily scientific phenomenon. Certain scientific phenomenon occurs within a very short period of time at different places. Using computer simulations will enhance development of student evaluation skills (Iqbal, 2012). Through replaying and stopping focus can be created on important parts. As such, students are able to understand a scientific phenomenon that would otherwise be difficult to understand in real time.

4.4 Depth and breadth of knowledge

Studies have demonstrated that computer simulations can improve the breadth and depth of knowledge through making abstract concepts become more concrete (Tawil & Dahlan, 2017; De Freitas & Oliver, 2006). The abstract concepts will be provided and made accessible to learners through computer simulation models. For example, the circulation system is a complex phenomenon, but this is simplified through a simulation model. According to Wall and Ahmed, (2008), computer simulations offer an opportunity to allow learners to represent visually and enthusiastically integral concepts that would be lost. Here, non-observable scientific phenomenon can be provided. Difficult scientific processes can be animated to enhance understanding which would not be enabled by textbooks. Basically, computer simulations allow students to visualize a difficult phenomenon.

Another important finding from research on computer simulations is through facilitating engagement in learning. Research has shown that there has been improvement in the level of students participation and motivation during preparations for simulation exercises (Thong et al., 2008). As such, computer simulations enable advancement of learning goals, process skills, discussions, argumentation and identification of science concepts. This was found to be consistent with other studies that have suggested that successful student engagement to computer simulations the learning process should be authentic and meaningful (Yas et al., 2014).

5. Conclusion and recommendation for further research

As shown by various researches, computer simulations are often geared towards acquiring skills. Therefore, exploratory learning being an approach of learning and teaching that inspires students to observe and examine original materials, enables students to unravel existing relationships between contextual knowledge and unacquainted content and ideas. Technological advances have shifted the perception of teaching through introduction of instructional learning approaches. Computer simulation is a computer-based program that creates things and relates them using a cause and effect connection. In this regard, computer simulation is a teaching and learning model, which can be used to present theoretical components in the real world, thus achieving the learning objectives. Although the use of simulations in e-learning is not an overly new concept, it has not been utilized maximally. Therefore, I propose that due to resistance to technology especially from tutors' stand-point, e-learning platform should be blended with the traditional method of instruction. Further, caution should be exercised while introducing such high level techniques like computer simulation since what has worked in other education systems may not work in the Kenyan curriculum context.

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An Adaptive Gamification Tool for E-learning Platform

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Abstract

Numerous studies have shown that many students taking the computer science programming courses due to its abstract nature easily get demotivated and disengaged along the way resulting to a high failure rate and dropout. In this paper, we discuss an innovative approach to programming pedagogy using gamification elements and mechanics in a Learning Management System (Moodle) to motivate students, improve their engagement and performance. Since students have different motivational factors determined by their preference and learning style, we discuss how Machine Learning Algorithms namely KMeans and K Nearest Neighbor (KNN) are used to classify students based on engagement level, progressively adapt to their learning behavior and recommend the right gamification elements based on the level of interactivity achieved.

Keywords: gamification, motivation, engagement level, personalized learning, machine learning.

1. Introduction

It has been noted in technical education students have been performing poorly and are usually not industry ready when they pass out (Naik & Kamat, 2015). There are a variety of reasons key been lack of personalization or individualized attention especially within the e-learning platform. This is usually manifested as demotivation and disengagement on the part of the student. The desirable behaviors in learning processes is to improve the level of learners' motivation which can be achieved through personalized gamification (Roosta, Taghiyareh & Mosharraf, 2016).

Play is fundamental component in cognitive development and learning as noted (Plass, Homer & Kinzer, 2015; Deterding et al., 2011). Play provides motivation among players, and can be used to establish engagement for learning, Digital games have the benefit of customization and personalization for adaptivity and provides an environment for risk taking and exploration. Games utilized in learning environment are serious games and gamification as shown in the game's taxonomy, Figure 1.

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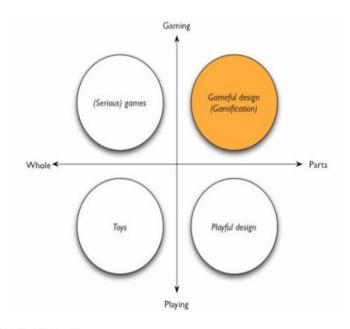


Fig 1: Classification of games

In this paper, we demonstrate how applying gamification to an E-learning Platform (Moodle) can improve motivation and student engagement in learning. This is achieved by designing a gamified e-learning system that uses Machine techniques learning to personalize gamification elements and adapt to learning style and personality. Currently, the gamification in place is created for a group of students without considering different motivational factors among learners.

This paper has been organized as follows: - Section II discusses the related work on player types, personality traits, learning theories and styles, motivation and game elements design.

Section III discusses the methodology used in the study and how Machine learning algorithms was implemented to get the tool for that worked on Moodle data to recommend appropriate game elements to students. Section IV presents the results obtained from the study and the performance metric. Section V highlights on the conclusions and future work recommendation.

2. Literature review

2.1 Gamification

Gamification is referred to as applying elements and mechanics of games in order to engage a user in a task outside of a game context (Ferro, Walz & Greuter, 2013). To investigate the impact of gamification on learners, studies have been made to understand ideal player types based on their personality. Psychologists for example, have identified that player typologies have relationships with that of pre-existing personality types.

Player types and personality

Some of the player types identified by researchers which contributed a lot in identifying player typologies used in current games are:- Socializer, Achievers, Explorers and Killers (Bartle, 2003, 2004), Competitor, Explorer, Collector, Achiever, Joker, Artist, Director, Storyteller, Performer and Craftsman (Fullerton & Swain, 2008), and Agon, Alea, Mimicry and Ilinx (Caillois, 1961). Personality refers to an inner tendency or predisposition for a person to act in a certain way (Berecz, 2009). The study of personality can be traced back to the work of Hippocrates and Galen (Crowne, 2009). In his studies, Eysenck (1970) dismissed their work and concluded personality is based on three super factors that comprise narrow traits which are Introversion or Exraversion, Neuroticicm or Emotional stability, and Psychoticism. Currently, the big five categories are used to evaluate human personality which are Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism, acronymed as OCEAN (Crowne, 2009).

2.2 Learning theories and styles

A taxonomy proposal by Smith (1999) depicts four orientation of learning theories and principles which are as follows. Behaviorism: - embraces conditioning and advocates rewarding and targets. Cognitivism concentrates on complexities of human memory and believe. Humanism focuses on experimental learning and finally Constructivism which relies on what is already know and understood by the learners.

Learning style is a consistent way of operating that indicates the underlying cause of a particular learning behavior. It shows how students learns and what they like to study (Hwang et al., 2012). The four learning style dimensions identified by Soflano, Connolly and Hainey (2015), and Khenissi et al. (2016) are: - Active/Reflective which describes how information is processed; Sequential/Global demonstrates the understanding by learners, Sensing/Intuitive highlights on how preference is perceived by learners to solve a problem and Visual/Verbal describes how information is retained and represented by learners.

2.3 Motivation

Motivation is a construct that explains the energy, persistence, direction and quality of behavior (Ryan & Deci, 2000). The scholars noted that people who are internally motivated perform better, have more creativity, persistence, vitality and general well-being as compared to those who are externally motivated. Self-determination theory (SDT) is one of the most fundamental theories of motivation which suggests three psychological needs of autonomy, Competence, and Relatedness. When the three needs are fulfilled, intrinsic motivation increases with the growth and development occurring. According to Roy and Zaman (2017), amotivated individuals are those who have no intention to perform a particular behavior whereas intrinsically motivated individuals are those that find pleasure interest and enjoy the engagement of the activity. SDT is a vital in the development of gamification as it allows for the development of various strategies in the design and implementation of gamification effort.

2.4 Game element design

Game can be defined as a way of play that has structure and goal (Strmečki, Bernik & Radošević, 2015). It comprises rules units and components that interact in a way to achieve the set goals. In other hand, game elements are described as the elements that characterizes a game, i.e. the features that describes the type of game and the way it is played (game mechanics) (*Ibid.*, 2015). Many gamification studies investigate impact of multiple gamification elements simultaneously which makes it difficult to correctly know the extent that these elements contribute to motivation and behavior (Mekler, Br[°]uhlmann, Opwis & Tuch, 2013). Design of successful gamification elements for e-learning systems require deep understanding of the concept of games i.e. goal focused activities, reward mechanisms and progress tracking (Strmečki, Bernik & Radošević, 2015). Naik and Kamat (2015), Roosta, Taghiyareh and Mosharraf (2016), Ferro, Walz and Greuter (2013), Mekler, Br[°]uhlmann, Opwis & Tuch (2013), and Codish and Ravid (2014) recommend gamification elements that are best suited for e-learning systems which are: points, badges, leaderboard, progress bar, levels, customization.

2.5 Machine learning techniques

Machine learning algorithms are useful in attaining adaptability and classifying students based on level of participation. Back propagation neural network was used by Ben, Darryl, Michaela and Ray (2008) to adapt to player character based on change in environment.

They also suggested use of radial basis to classify players. Fuzzy logic was used by Xu, Wang and Su (2002) to model student profiles and by Kavi et al. (2003) to evaluate learning objectives and outcomes. Other ML techniques used are Iterative Dichotomiser 3 (ID3) for predicting students' performance (Adhatrao et al., 2013), Self-Organizing Maps (SOM) with Back Propagation to establish the connection between learners objectives and learners needs and come with appropriate for each user (Beetham & Sharpe, 2013), Bayesian Network (BN) to categorize users and quantify if a student can complete a certain activity (Mora, Riera, Gonza ´lez & Arnedo-Moreno, 2017), student behavior prediction using Hidden Markov Model (Morteza, Maryam & Anari, 2012) and Genetic Algorithm (GA) can be useful when it comes to understanding end user preference, want and needs (Drigas, Argyri & Vrettaros, 2009). Due to our relatively small dataset, K-means was used for clustering students and KNN for classifying students adaptively based on how student engage in Moodle platform.

3. Methodology

This study employed Design Science Research Methodology (DSRM) because of the rigor its employs for evaluation, concentrated design and development stage. In relation to this study, the process used is as listed as below:

- Problem identification and motivation the problem is having a gamification tool that will improve the motivational level of learners studying basic programming. The tool needs to cater for the difference in motivation and learning style among students and adapt to their personality.
- Objective of the solution definition This involved Identifying gamification elements that are best suited to motivate students based on their preference and personality. It also required to progressively adapt to their learning behaviour.
- Design and Development Develop a LMS prototype that will use AI techniques to adapt to users preferences and recommend the right gamification elements. The aim was to enhance motivation and engagement.
- Demonstration Involved applying the tool to a sample size of computer science students to demonstrate its work-ability and applicability.
- Evaluation Involved evaluating the results against the problem stated to identify their efficiency in improving motivation and engagement.
- Communication Involved communicating the performance of the prototype and the results obtained after evaluation. Finally, the findings are to be published.

The end product was an adaptive tool embedded within the LMS prototype that uses AI techniques to adapt to users preferences and recommend the right gamification elements to enhance motivation and engagement level.

3.1 System architecture

In this architecture, the adaptive tool is linked to the Moodle backend where individual user data is retrieved from the logs. System interactions for the user are mined and an evaluation of learning behavior is determined. This evaluation is passed to the classification algorithm which classifies the user, based on evaluation made, to one of the identified clusters, and its value is recorded. This value, together with student evaluation, is passed to the recommended module which provides the appropriate gamification elements. This process is done progressively as the student interacts with Moodle and from the evaluation, the recommender module adapts to the user's level by recommending elements that suits the user at that level (see Figure 2).

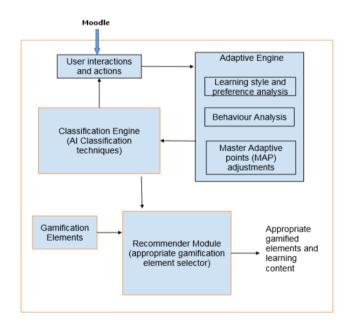


Figure 2. System architecture

3.2 Pre study

Mining of data was done from logs of a live e-learning platform to be the training data for the ML algorithms used. A total record of 89,000 were extracted cleaned, transformed to appropriate format and loaded to a clustering algorithm (K-means). The base clusters generated were 4 as shown in Figure 3.

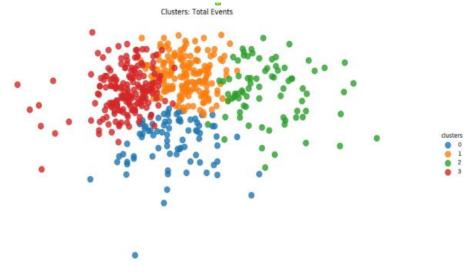


Figure 3. Clusters identified

Cluster interpretation and gamification elements used

• Achievers - students who were most of the time ahead of others. They clearly dominate the top. Gamification elements used: - Level Up, Stash, Progress bar, Badges (Cluster 1)

• Disheartened students - Students that started the course at rates, similar to Achievers, but soon fell behind and stabilized with a lower acquisition rate. Gamification elements used: - Level Up, Progress bar, Ranking (Cluster 3)

• Underachievers - Students, typically with the lowest participation and must have had a lower level of interest and engagement with the course. Gamification elements used: - Level Up, Leaderboard, Progress bar **(Cluster o)**

• Inquisitive (Explorer) - users like to explore and investigate new things. They are be more inclined to engage with open worlds, be in control and embark on quests to locate particular items. Gamification elements used: - Level Up, Stash, Hidden picture, Badges (Cluster 2)

3.3 Implementation

The main course that contains all the learning course content is created in Moodle. All the users will have access to this course through four hidden sub-courses interlinked to the main course at the back end. Each sub-course holds students enrolled based on the personalization determined by the classifier. The sub-courses also represent the identified clusters where each cluster has its own defined gamification elements. These elements are then integrated to the sub-course making all the users enrolled in them to have access to the elements. The class activities however are created and attempted by participants through the main course to avoid content duplication. This makes it as the core course for utilization by the ML algorithms. The individual logs for each participant which are recorded in the main course becomes the input for the classifier algorithm which works on the logs and determines the personalized game profile (cluster) for individual student. Since the sub-courses are hidden, the users can only see the main course and cannot tell the difference in content allocation, but will notice the game elements accessible in their profile are different. The game element recommender module enrolls the student to the right sub-course (cluster) once they attain the recommended Master Adaptive Points (MAP) for that cluster. Each sub-course has been installed with the right game elements.

Adaptivity

The system initially doesn't know which cluster each student belongs to. They are all enrolled to the main course. As the user interacts with the system, the adaptive engine evaluates traits and behavior of the user and passes the identified data to the classifier. The classifier evaluation the sent data and returns the identified MAP attached to the user. The MAP change is monitored every now and then to identify attainment on the recommended score. If so, the student is unenrolled from the current course to the sub-course which has the right game elements. The first enrollments may not be accurate because there are few logs for each student but this is perfected with time as student interacts with the system. The enrollment to different sub-courses is progressively made as the engagement level of the students increases. This ensures that the right gamification elements suitable for the level classified are always availed to them. The parameters used to measure the success of the tool were:

• Enrollments made to different clusters – This meant there was improvement in engagement level as the student got access to personalized game elements.

- Feedback got from questionnaire administered on pre and post study.
- 4. Testing, results and discussion

To test the tool, two classes of computer science students at Kenyatta University were subjected to the study. The two questionnaire administered to students before and after study showed significant improvement in students responses after they interacted with the gamified platform. Students of age group 21-25 and 26-30 were the most participants and used laptop and smartphone to access the online platform with a percentage of 29.64 and 28.46 respectively.

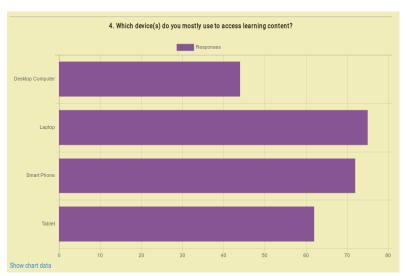


Figure 4. Devices used to access platform – Kenyatta University Moodle Platform

Out of the responses, 139 acknowledge that they do play games and 68% denotes that playing a game can assist them in learning. This number increased to 74% after being subjected to a gamified system as shown in Figure 5 and 6.

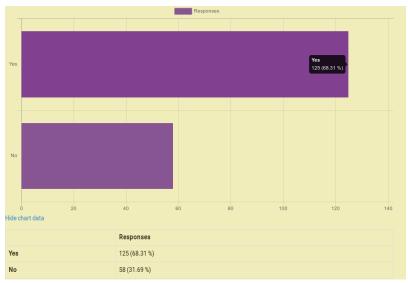


Figure 5. Pre-study analysis on impact of game in learning – Kenyatta University Moodle Platform

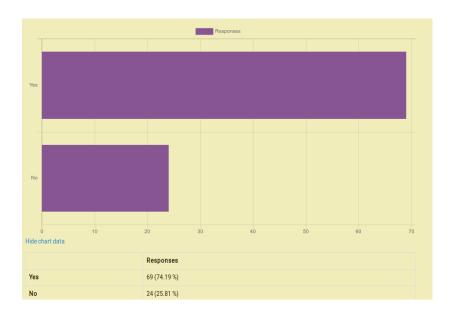


Figure 6. Post Study analysis on impact of game in learning – Kenyatta University Moodle Platform

Classifier grouped students at real time and assigned them to respective clusters. An improvement in cluster allocation was evidenced within the first week of system interaction as shown in figure 7.

The system started off with allocation of 116 students in the underachievers cluster, 35 disheartened and 7 achievers. In one week's time, the numbers continuously adjusted at real-time with 6 newly adapted underachievers identified and disheartened group increasing to 50.

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Figure 7. Pre and post study classification output

Gamification tools also showed great motivation among students. In one group, students had attained over 11,000 experience points which were attained by interacting with the system. The leaderboard made students to keep their position on top (see below) but wasn't the case for everyone. Some were motivated by ranking based on certain aspects while others were just okay without the elements. All these were provided to cater for the difference in their motivational factors.

Rank	Level	Participant	Total	Progress
1	1	ADHIAMBO HELLEN O	11,136 ^{xp}	8,509 ^{xp} to go
2	1	LANDO ELVIS O	11,085 ^{xp}	8,560 ^{xp} to go
3	1	Dr. Tom Destiny Namwamba	10,533 ^{xp}	9,112^{xp} to go
4	1	WAFULA RUSSEL A	10,500 ^{xp}	9,145 ^{xp} to go
5	6	KATUMBI KYENGO A	9,207 ^{xp}	1,027^{xp} to go
6	6	IRENE OMONDI	7,743 ^{xp}	2,491^{xp} to go
7	6	SOLOMON ODUNDO B	7,647 ^{xp}	2,587 ^{xp} to go
8	6	AHMED ZENA A	7,488 ^{xp}	2,746^{xp} to go
9	6	MITATI AMBROSE K	7,086 ^{xp}	3,148 ^{xp} to go
10	6	GIKUNYI NJERI S	6,954 ^{xp}	3,280^{xp} to go
11	6	KITHIA WAMBUI S	6,555 ^{xp}	3,679^{xp} to go

Figure 8. Leader board game element - Kenyatta University Moodle Platform

Ranking details: First 97 students					
	Separate groups All participants				
Pos	Fuliname	Points			
1	KIMANZI	166.0			
2	WYCLIFF WYCLIFF	159.2			
3	🕵 TWALET,	158.0			
4	MALETO	157.5			
5	YVONNE	141.9			
6	MBURUKU S	115.6			
7	Rachel Jikwanyi	101.8			
8	MICHAEL	97.5			
9	LANSON WAMBUI	93.0			
10	ISSACK	92.5			
11	MARIITA	85.5			
12	🚮 gitau	85.0			
10		70.0			

Figure 9. Ranking game element – Kenyatta University Moodle Platform

Some games were implemented as well to enhance motivation and monitor if they will have impact in learning. These games include crossword which challenged students to master terminologies in the unit. It was observed that students were participating even at odd hours and their level of engagement helped them gain experience points and be classified to other clusters.

5. Conclusion and future work

As seen, using gamified platform is indeed necessary for keeping students engaged in online platform. The gamified system used should not just focus on general game elements for students but personalized ones and keep adapting the student's learning behavior as motivation kicks in. When personalization is in place, boredom is also eliminated. As per objectives of this study, we were able to identify gamifiction elements suitable for recommending to learners according to their learning behavior, apply appropriate AI techniques to cluster students based on their behavior and progressively classify them and finally create a platform for implementing these features. However, using ML packages in some servers became a challenge because of restriction access and the ability of the server to run the classifier as fast as it could. Using other classifying methods such as neural network and deep learning were not viable because of the small data-set obtained. This caused the algorithm to over fitting with every trial. In future, other efficient ML techniques will also be applied as access to a large dataset is availed and the gamified tools to be integrated with other LMS platforms.

Acknowledgements

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The authors declare no competing interests.

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A Systematic Mapping of Adaptive Gamification in E-learning

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Abstract

Gamification has gained currency in the recent past and has widely being deployed in various disciplines such as health, education, marketing amongst others. The main driving factor of deploying gamification is due to motivational element. Gamification, particularly in education, has been used to motivate and elicit engagement in learners. However the implementation of gamification within e-learning platforms has been of the "*One size fits all*", i.e. uniform application of gamification elements to all learners, however learners possess different characters which are distinct from each other. The need to embrace "*One size does not fit all*" approach necessitates introduction of adaptive gamification. This study sought to establish the state of the art of adaptive gamification applied within e-learning using a systematic mapping approach. The study identified 122 studies and distilled to final 23 for detailed review and mapping. The study found out that gamification elements are mostly used as structural gamification, with basis of adaptivity been predominately static and the methodological implement been mathematical. Overall it was found that adaptive gamification has positive effect within the e-learning platform

Keywords: gamification, e-learning, adaptive, systematic mapping, motivation.

1. Introduction

Gamification as has rapidly expanded due combined influence of ubiquitous sensor and mobile technology, growth of digital games been a cultural norm, market and business model orienting towards customer centrism and finally public policy makers realization for need to motivate and engage members of the public (Nacke & Deterding, 2017). Consequently, these technical, political, economic and cultural forces propelled by the need for user engagement and motivation birthed gamification phenomenon (Nacke & Deterding, 2017). "Gamification" as defined by (Deterding, Sicart, Nacke & K., 2011) is the use of game design elements in non-game

© **Authors**. Terms and conditions of Creative Commons Attribution 4.0 International (CC BY 4.0) apply. **Correspondence**: Samuel Kamunya, South Eastern university Kenya, School of Information Technology, Nairobi, P.O. Box 170-90200, Kitui, KENYA. E-mail: <u>smuthee@seku.ac.ke</u>.

context and they opine that gamification is distinct and separate from serious games, video games. (Lee & Hammer, 2011) define gamification as the use of game mechanics, dynamics, and frameworks to promote desired behaviours. Gamification outlined by (Kapp, 2012) is use of gamebased mechanics, aesthetics and game thinking motivate action, promote learning and solve problems, whilst Huotari and Hamari (2012) define gamification as a process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation. Seaborn and Fels (2015) opine gamification as the intentional use of game elements for a gameful experience of non-game tasks and contexts. Game elements are patterns, objects, principles, models, and methods directly inspired by games. The view taken by Harman, Koohang and Paliszkiewicz (2014) on gamification that it's a discipline widely used in marketing, extended to other areas such as health, environment, government and education. Lee and Hammer (2011) provide a basis for use of gamification in education in that its, motivates student to engage in classroom, give teachers better tools to guide and reward students, facilitate immersive learning, while Simões, Redondo and Vilas (2012) opines gamification in education aims to increase people's engagement and to promote certain behaviors. They argue that the key contribution of gamification in education is to increase the level of engagement of students. Deductively therefore, the aim of gamification in education is to extract the game elements that make good games enjoyable and fun to play, adapt them and use those elements in the teaching processes. Thus, students learn, not by playing specific games but they learn as if they were playing a game.

In education content delivery is of vital importance. There are various forms including the traditional classroom face to face, flipped classroom, blended learning, distance learning and E-learning amongst others. In education, E-learning is a vital tool in pedagogy. E-learning described by Wang and Chui (2011) is a learning mode which encompasses web-based technologies or virtual learning environments in which learning process can occur electronically anytime and anywhere via the internet or intranets. They state the importance of virtual learning is due to the advantages of efficiency in transferring knowledge, learning environment customization according to specific individual needs and learning styles, adaptability for multiple forms of interactive learning, time flexibility, allowing pauses at specific points and, if necessary, repetition of specific parts, enabling autonomy of self-evaluation processes and allows having a greater number of students. In many learning environments, pedagogy assumes that all learners are of homogeneous characteristics. However, Naik and Kamat (2015) argue that individualized or personal training is of immerse benefit to the learner, due to the fact that all learners differ in preference, style and abilities with regard to the learning processes with or without technology mediation. Failure to take cognizance of this leads to learner disinterest, frustrations and disengagement. Gamified e-learning systems have been fraught with failure due the uniform distribution of gamification elements amongst learners, i.e. "one size fits all" (Roosta, Taghiyareh & Mosharraf, 2016). This dictum has been countered by Nacke and Deterding (2017) who advocate for "one size does not fit all", since learners are unique in learning characteristics, individuality and learning approaches. Schöbel and Söllner (2016) claim that most gamification projects are not working, because they are designed for a crowd of system users without considering the personal needs of each user. To motivate system users and to make an information system appealing to them, it is necessary to focus on system users and their individual preferences through a suitable gamification element design (Burgers, Eden, Engelenburg & Buningh, 2015; Ha-mari & Koivisto, 2015). Beyond overcoming the quite obvious problems, it seems promising to enhance the effectiveness and success of gamification by tailoring the gamification elements to the individual preferences of users (Smalls, 2013). Hence, it is necessary to develop individualized gamification designs that provide adaptivity of gamification elements focusing on personal needs (Cheng, Lin & She, 2015). Indeed, Burgers et al. (2015), Roosta, Taghiyareh and Mosharraf (2016) argue this challenge is overcome through suitable gamification design elements of matching the systems users to their preferences. Cheng, Lin and She (2015) affirms by recommending that games and gamification projects should aspire to have an individualized design for adaptive elements for

personalized needs. Further, Codish and Ravid (2014) posit for the need of adaptive gamification for successful gamification projects. E-learning platforms are amenable to implementation of gamification. Comprehensive systematic literature review on gamification in e-learning (Dicheva & Dichev, 2015; Ortiz et al., 2016) has been conducted, revealing the potential and impact accorded to learners. Many initiatives towards adaptivity of gamification within e-learning platforms have been initiated and evaluated revealing varying degree of success and impacts. As a nascent research area there has been but two comprehensive reviews by Böckle, Novak and Bick (2017), and Stuart, Serna, Marty and Lavoué (2019), but no systematic mapping study, as such the study seeks to address this gap.

The remainder of this paper is structured as follows: Section 2 describes the systematic mapping process; it presents the research questions and the search string, along with the inclusion and exclusion criteria and data extraction process. Section 3 reports the results obtained from the mapping process. Section 4 discusses the main findings, states the limitations of the studies and outlines the implications for practice and research. Our conclusions and future work are presented in Section 5.

2. Systematic mapping process

In systematic mapping aim is to provide an overview of the research area identifying the quantity, type and results (Petersen, Feldt, Mujtaba & Mattsson, 2008). The focus of this study is to provide an overview on the state of adaptive gamification within e-learning platforms. Dalmina, Barbosa & Vianna (2019) elaborate that the goal of a systematic mapping is to insightfully provide a state of art in a focus area, identifying the key trends and revealing the research gaps.

The purpose of this study is to determine and characterize the state of the art of adaptive gamification in e-learning, analyzing the existing proposals and research work and thus identifying potential gaps and opportunities for future research. The main research question guiding this study is therefore:

What is the state of the art of adaptive gamification applied to e-learning?

In order to conduct the systematic mapping process, the researcher followed steps elaborated by Petersen et al. (2008): (i) definition of research questions, (ii) performing the search for relevant primary studies, (iii) screening of papers, (iv) key wording of abstracts, and (v) data extraction and mapping.

2.1 Definition of research questions

The study was carried out in last quarter of 2019 and covered the period 2014 -2019. The summary of questions in as tabulated in Table 1.

Table 1. Research questions		
ID Research Question		
RQ1: In which context of e-learning has adaptive gamification been applied?		
RQ1.1. What types of courses and education level have been implemented in adaptive		
gamification?		
RQ1.2. which educational activities have utilized adaptive gamification?		
RQ1.3. what is the nature of adaptive gamification?		
RQ2: How has Adaptive gamification been implemented in E-learning platforms		

RQ2.1. Which gamification elements have pre-dominantly being adapted?

RQ2.2. On what basis has adaptive gamification been implemented?

RQ2.3. What kind of Methodologies/tools/instruments have been used to implement

the adaptive gamification?

RQ3: What is the evidential impact of Adaptive gamification on e-learning?

RQ3.1. What the outcome of adaptive gamification is as deployed within e-learning

Platforms?

RQ1 seeks to understand the environment in which the adaptive gamification was implemented specifically the course implemented, education level, which educational activities and nature of gamification adaptation.

RQ2 sought to examine in detail the nature and implementation of the adaptive processes starting the game elements or mechanics deployed, the basis of adaptivity and the methodologies employed to realise the adaptation process.

RQ3 examined the evidential impact of adaptive gamification effort. Whether it resulted to positive, negative or neutral outcomes.

2.2 The search and study selection process

In- order to achieve the objective there was need to identity the list of databases to search, they included IEEE explore, Science Direct, ACM digital library, Google scholar, Springer link, since these databases contain numerous to filter and gather the specific information there was need to develop a search string

The research string was:

Gamification captured as *gamif*^{*} *OR game elements*. Gamif^{*} as a wild card for gamification, gamify, gamified,

AND

Adaptive captured as (adapt* OR personali* OR individual*) for the wildcards for adaptive, adaptivity adaptable. Personal wild card for personalisation, personalized and individual for individualized or individualization,

AND

E-learning Platform as "(e-learning OR Virtual learning Environment OR online learning OR Learning management systems)".

The selection process of primary studies was composed of two screening stages. During the first stage, the titles and abstract were read to measure relevance. During the second stage, the full text was read to make a decision on inclusion or exclusion. To avoid the premature exclusion of studies, doubtful studies were always included for further and detailed reading during the second stage. The inclusion and Exclusion criteria as elaborated by Petersen, Vakkalanka and Kuzniarz (2015) was:

Inclusion criteria:

- INC1 Academic journal, conference and workshop papers which are peered reviewed

- INC2 Studies are in the field of adaptive gamification in e-learning.

- INC3 Studies present the research method and results

Exclusion criteria:

- EC1 Studies dealing with Adaptive serious games or adaptive game-based learning or not explicitly using adaptive gamification within and an elearning Context.

- EC2 Studies presenting summaries of conferences/editorials or guidelines/templates for conducting mapping studies.

- EC3 Studies presenting non-peer reviewed material.
- EC4 Works not written in English
- EC5Works not accessible in full-text
- EC6 Books and gray literature

The search and selection process is illustrated in Figure 1.

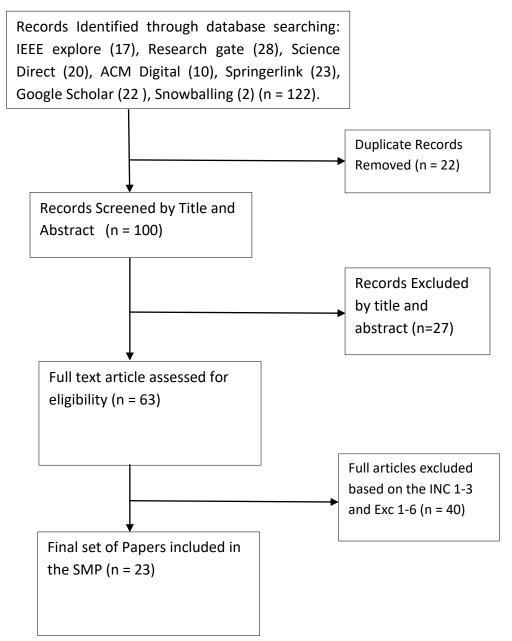


Figure 1. Study selection process

Our search identified 122 papers. After removing duplicates 100 papers remained. Of these 23 were removed based on screening of title and abstract. The remaining 63 articles were considered and assessed as full texts. 40 did not pass the inclusion and exclusion criteria. 23 final eligible studies remained and were individually assessed for this systematic mapping study.

2.3 The data extraction process

To extract data from the primary sources identified, we followed the guidelines of Petersen, Vakkalanka and Kuzniarz (2015), Alhammad and Moreno (2018) that had the following steps design the data extraction template, data extraction and its validation. The key fields were:

• Research Type: The following classifications were adapted from (Petersen and Feldt, 2008) to the education field in order to record the type of research reported in the primary studies:

- Evaluation research: A study reporting adaptive gamification applied in e-learning course, where evaluation is conducted in a real setting e.g. classroom.

- Validation research: A study reporting adaptive gamification applied in e-learning course where the gamified solution was validated in a laboratory setting (e.g., a pilot study, experiment with volunteer students).

- Solution proposal: A study proposing an adaptive gamified solution for an elearning course that was neither evaluated in a real setting nor validated in laboratory environment.

- Experience paper: A study reporting the authors' experience, reflections, benefits and drawbacks of adaptive gamification of e-learning platform.

- Philosophical papers: A study describing a new conceptual idea, implying a new way of adaptive gamification.

- Opinion paper: A study reporting the authors "opinion" about applying adaptive gamification rather than describing a new result of applying adaptive gamification as a novel design, or a conceptual idea.

• What types of courses and education level have been implemented in adaptive gamification

• Which educational activities have utilized adaptive gamification that is, the type of educational activity, such as projects, assignments, lectures, etc. that has been gamified.

• What is the nature of adaptive gamification, how has adaptivity been implemented using static, dynamic approach.

• Which gamification dynamics, mechanics, and elements have pre-dominantly being adapted.

• On what basis has adaptive gamification been implemented, used learning style which model FLSM/ KOLB, personality MBTI personality, gaming behavior Bartle model, Andrezwicki hexad brainer scale

• What kind of tools/instruments have been used to implement the adaptive gamification, how is adaptivity implemented using some matrix, machine learning, algorithms, mathematical formulae.

• Purpose of applying adaptive gamification, recording information about the aim or reason behind adaptive gamification, do the authors want to improve student performance, motivation, etc.

• Gamification impact, gathering information regarding the evidenced effect of applying adaptive gamification in e-learning

Data Item	Value	RQ
Study ID	First author's last name + year of publication	
Article Title	Name of the article	
Author Name	Names of all the authors	
Year of Publication	Calendar year	
Venue	Name of publication venue	
Type of Research	Evaluation research, solution proposal, validation research,	experience paper,
	philosophical paper, or opinion paper.	
Type of Course	What is the type or format of the gamified course?	RQ1.1
Adaptive gamified	Which educational activities/components have utilized	
Activity	adaptive gamification?	RQ1.2
Nature of adaptivity	How has adaptivity been implemented using Static or	
	dynamic adaptive gamification approach?	RQ1.3
Adapted game	Which gamification dynamics, mechanics, and elements	
Elements	have pre-dominantly being adapted?	RQ2.1
Basis of adaptive	Which approach was used for adaptivity learning style	
	Personality, gamification, Player?	RQ2.2
Methodological	How has adaptive gamification implemented the tools,	
Approach	Mathematical formulae, Machine learning algorithms,	RQ2.3
Impact of Applying	Was the impact of applying adaptive gamification in	
Adaptive gamification	e-learning positive, negative, or neutral?	RQ3.1

The Data Extraction Form

2.4 Data analysis

During the data analysis, the information of each item extracted was tabulated and grouped according to their values, providing the information required to generate the figures and tables presented in Section 3. To generate the statistical data, the papers belonging to each group of an item were counted. Throughout the study, the papers were organised under the classification categories, corresponding to each of the research questions of the systematic mapping, including focused and statistical questions.

2.5 Validity evaluation

As with any systematic review or systematic mapping studies a number factors that may affect the conclusions drawn, i.e. threats to the validity as defined by Petersen, Vakkalanka and Kuzniarz (2015), Alhammad and Moreno (2018), key amongst them are:

(1) Descriptive validity the extent to which observations are described accurately and objectively this overcome using the data extraction template.

(2) Study Selection: This threat concerns the possibility of researcher bias and author disagreement on exclusion and inclusion. We applied a strategy to deal with this threat. We deployed the inclusion and exclusion criteria for identification of acceptable studies.

(3) Search Coverage. This threat concerns the completeness of the search process and the preventive measures taken to avoid leaving out relevant studies by using a broad exhaustive search string in well recognized databases.

3. Results

3.1 General results

This section reports the general finding relating to the primary studies. Figure 2 illustrates the distribution of studies yearly. The period of study was from 2013 to Oct 2019. The publications on adaptive gamification have picked up from 2016 indicating more research focus. Figure 3 focuses on the distribution avenues of the studies, without doubt conference take a significant share at 61 % since they are usually the turnaround duration is less as compared to journals at 35% and workshop 4 %. Figure 4 describes the research type conducted in respect of adaptive gamification, it reveals both Evaluation and Solution proposal studies even matched followed by validation research and lastly philosophical study. The Evaluation studies consisted of developed adaptive platforms tested in actual classroom environments while validation studies were adaptive platforms though tested on voluntary limited basis.

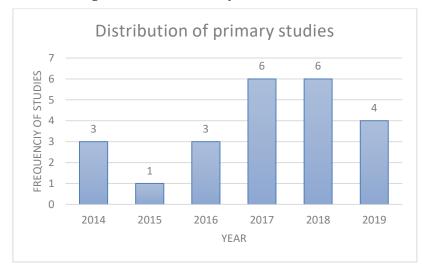


Figure 2. Distribution of studies yearly



Figure 3. Distribution of publication venue

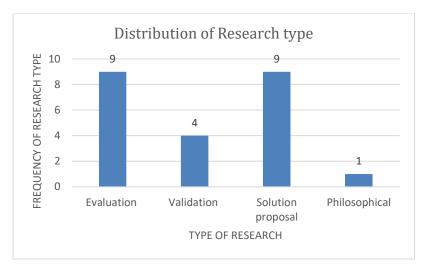


Figure 4. Distribution of type of research

3.2 RQ1 - Context of application

The section deals with the type of course, which activity utilizes the adaptive gamification and the nature of adaptive gamification

3.2.1 RQ 1.1 - Type of course

The results show that nearly 50% (11 studies) do not state which courses the course platform has been adaptively gamified. The STEM courses especially Computer Science courses are most pre dominate this probably attributable to the researchers back ground and ease of access to the experiment study area. A few studies focussed on languages [A6, A7, and A16]

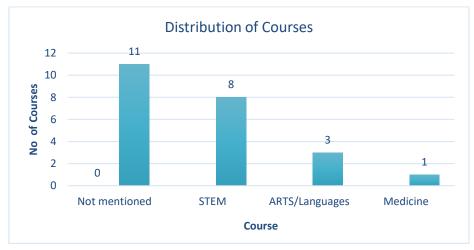


Figure 5. Distribution of courses

3.2.2 RQ 1.2 – Educational activity

The research question examine which activity was adaptively gamified there were four key classes. The most adaptively gamified activity was learning (Materials presentation, Assignments, quizzes Chats quizzes), next was both Group formation [A1, A8] and also social networking activities were also gamified [A11, A21]. Finally, 3 studies focused on mentoring.

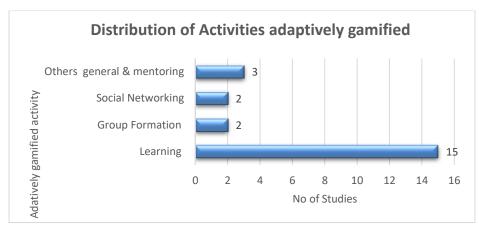
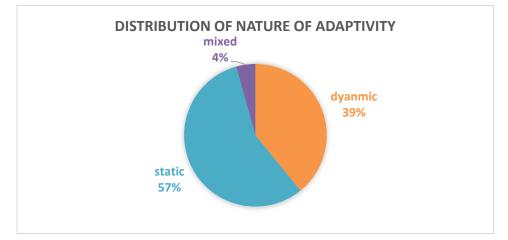
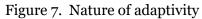


Figure 6. Activities adaptively gamified

3.2.3 RQ 1.3 – Nature of adaptivity

The question examined how adaptivity was implemented either statically, whether the gamified status of the user is determined once mostly by use of questionnaires or dynamically where the system automatically recognizes the user through various approaches (user data, usage data) to create a profile and adapt the system on the derived profile. It should be noted though this profile discovery can be done once or continuously during the usage of the system. In the static approaches the system made use of validated instruments for profile creation, such as MBTI for Personality profiles, HEXAD brain type for gamification profiles, FLSM for learning styles, as such the user was requested to answer some questions which lead to his profiling. The results show that 57% of the studies had static nature of adaptivity as opposed to 39% which utilized dynamic approach to adaptive gamification which required the development of adaptive engine. One study [13] deployed mixed approach starting of using static method but the user profile is dynamically update with use of the system





3.3 RQ 2.2 – Basis of adaptive gamification

The goal of this section is to examine how adaptivity gamification was implemented, which gamification elements were used, the basis of adaptivity and the approach deployed.

3.3.1 RQ 2.1 – Gamification elements

In the discussion of elements, we ascribe to the MDA framework that dissects the components of game. (Werbach & Hunter, 2012) elaborates this framework in the light of gamification as mechanics as "the processes that drive actions forward", a game dynamic can be defined as a pattern of loops that turns them into a large sequence of play and the components the specific elements. The Figure 8, bundles and summaries the three main items of the framework and bundles each of the instances into the three main items. By far elements (avatars, points, badges etc) are the most prevalent, followed by the mechanics (challenges, feedback, competition) and the least is dynamics (narratives, emotions). It reveals more effort is required to incorporate dynamics in gamification which is meaningful.

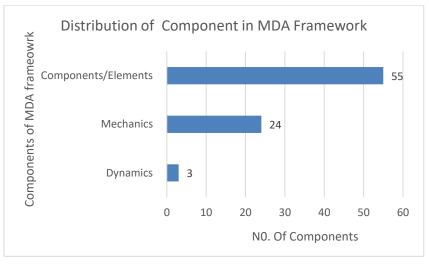


Figure 8. MDE Distribution

3.3.2 RQ 2.2 – Basis of adaptive gamification

This is a critical question on how adaptive gamification was implemented. For Adaptivity to be implemented a suitable method of matching the user and game elements must be deployed. The approaches are learning style of the learner, Personality of the learner, Player profile of the learner or gamification profile or the learner.

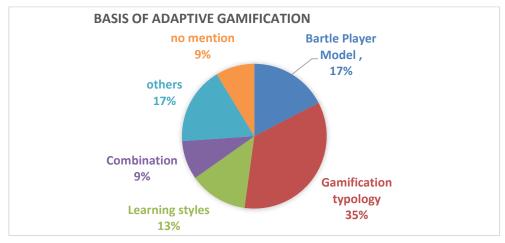


Figure 9. Basis of adaptivity

From the results the most predominate approach is gamification typology (35%) using the Hedax Brain scale, followed by the battle player model (17%), with learning styles (13%) basis specifically the FDLMS approach method. Some the studies used a combination of approaches such learning and player model approach. In the others category this constituted the timer approach, attractiveness index of the element, collaborative approaches in recommender systems.

3.3.3 RQ 2.3 – Methodological approach

In the research question the focus is how the identified adaptivity approach (gamification typology, Player model, learning styles) are implemented. From the study the most prevalent method is the mathematical modeling approach which uses either algebraic functions or matrices. In machine learning approach (26%) the emphasis is usually on supervised learning (classifiers) and unsupervised (k-Means). For the others segment (17%) the use tabular and adaptation rules.

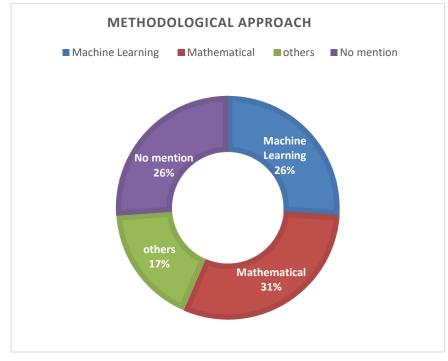


Figure 10. Methodological approach

3.4 RQ3 – Impact of adaptive gamification

The ultimate focus of adaptivity is whether there is contribution to enhance performance in learning such as more motivated students who are better engaged leading to better academic performances. Adaptive gamification is a novel idea where we seek to provide well suited game elements to elicit better intrinsic motivation and responses. From the studies reviewed, adaptive gamification does have a positive impact (84%). However, does not mean that adaptive gamification is a panacea to learning challenges, however its indicative that if well implemented its has great benefits to the learner. There is need for more effort required to ensure that adaptive gamification is effectively utilized in e-learning platforms.

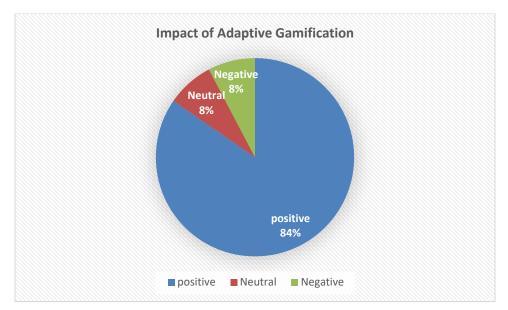


Figure 11. Impact of adaptive gamification

4. Discussions

From the results obtained the reviewed has revealed that much work has been done and accomplished of e-learning incorporating adaptive gamification.

Research questions 1, the context of adaptive gamification. From the study we can deduce that STEM courses have been better studied as opposed to the ARTS courses. Learning activities have greatly benefitted from adaptive effort and finally adaptive basis has been static as opposed to dynamic. Its recommended that emphasis been on dynamic adaptation since in the static approach consider time is spent in user profiling processes and may lead to learner disinterest, hence more subtle way is demanded that still provides the requisite information for data handling.

Research questions 2. Pertaining to the basis of adaptive gamification, the study has revealed game elements are the most used components, however there is need to introduce enhanced learning experience through more mechanics and dynamics through meaningful gamification that is user centered. As noted, it's vital to ensure that adaptive gamification moves from structuralist mode and adopt meaningful gamification that is based on user centred design framework. As for the basis of adaptivity the most preferred is gamification typology profile with player model been the next best option, however it's recommended that a combination of the two or more adaptive basis would give a better outcome. In respect of the methodological approach the utilized approach is mathematical models such matrices and algebra. However, there is need more use of machine learning techniques are they offer apt in dealing with user dynamism, hence consider using gamification analytics and learning analytics to give grounded approach for adaptivity

Research question 3, revealed that adaptive gamification has positive outcomes or positively influences in the area of study. However, contexts are different there is need therefore to find whether adaptivity is context specific of game elements, learner preferences and whether gamification can result in collaborative or competing outcomes for students. Still the sample of the studies is few and also there is need for longer study periods afforded by longitudinal studies.

5. Conclusions and recommendations

Adaptive gamification has gain prominence in e-learning platform, hence the need to review and understand its effectiveness and impact the study was a systematic mapping research, in which we identified 122 articles and distilled to 23 articles for consideration. These papers were investigated using 3 research questions focusing on the context in which adaptive gamification is deployed, the basis of adaptivity and the impact of adaptive gamification within the e-learning context. It revealed that learning activities are the most adapted activities in the e-learning platform, within adaptivity been predominately static. Further it revealed that there is need for more use higher gamification dynamics and mechanisms than the rudimentary mechanics. With respect to basis of adaptivity the study show that gamification typology is most predominate with mathematical models as the most preferred methodological approach. This call for researchers to embrace new adaptive approaches which can combine two or basis of adaptivity and also consider enhance use of machine learning techniques for methodological implementation. Overall the study reveals that there is a positive impact of adaptive gamification in e-learning however there is also need to review the negative effects.

In conclusion adaptive gamification does have positive impact within the e-learning platforms, though still at its infancy. In particular there is need for cognizance that learning is individualized hence there is need to account for learner individuality and design system which are adaptable to them for enhanced gamified e-learning platforms

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