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Considering learning styles and context-awareness for mobile adaptive learning

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Abstract Mobile devices are becoming ubiquitous in our society and more so with school aged children. In order to get the most out of the portable computing power present at students' fingertips, this paper proposes an approach for providing mobile, personalized course content tailored to each individual's learning style while incorporating adaptive context awareness. The respective approach has been implemented as an iOS application and the results of an evaluation with 45 students show that students were able to improve their comprehension of a subject matter by 23 % after using the application. The evaluation further demonstrated that not only is personalized mobile adaptive learning a successful method of instruction, but it is also very popular with the students who have used it.

Keywords Intelligent context-aware learning system · Mobile learning · Ubiquitous learning · Context awareness · Adaptivity and personalization · Learning styles

1 Introduction

E-learning, and by definition mobile learning, is being touted as one of the most significant developments in the information systems industry [31]. It has revolutionized and challenged traditional roles and models within the educational framework [31]. The ever-changing and increasing variety of locations where students learn, has led to serious technical and contextual challenges. Mobile learning is becoming widespread, where students are no longer limited to where they can learn [30]. Mobile and pervasive

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technology offers the possibility of creating innovative learning experiences that can take place anytime and anywhere [24].

Considering the fact that people learn in different ways and have different learning styles has been shown in the past to yield positive results when applied to desktop-based learning settings [11, 21, 26]. These results were in the form of increasing learning satisfaction, improving grades and decreasing time required to acquire new information. However, the role of learning styles as they relate to the usability in mobile learning environments has not been extensively investigated [6, 31]. Furthermore, with the ubiquitous nature of mobile devices, contextual awareness also plays an important factor in one's learning when viewed from a mobile point of view. Devices are used under many different conditions and locations, many of which may not be conducive to learning, and this needs to be taken into consideration.

The aim of this research is to contribute to the field of hypermedia and multimedia by introducing an adaptive approach for learning in mobile settings, which considers a learners' learning style as well as his/her context information for determining the most appropriate learning format to be presented to the learner. Adaptive eLearning systems such as adaptive hypermedia have tailored experiences for learners using the system's internal logic to create a specific model of the learners' needs and use this model to provide learners with adaptive learning experiences [17]. The goal of this research is to provide not only adaptivity in a mobile setting based on a learner's particular learning style, but also to consider the learner's physical contextual environment for determining the optimal format in which the course should be presented. In this paper, we analyse and demonstrate the effectiveness of such an adaptive mobile system with respect to learner satisfaction and improvement of knowledge.

To consider learners' learning styles in the proposed adaptive mobile system, the Felder-Silverman learning style model (FSLSM) [7] was selected. While there exists many learning style models in literature such as the learning style model by Kolb [14] and Honey and Mumford [12], this research work uses the FSLSM for several reasons. FSLSM combines several major learning style models such as the learning style model by Kolb [14], Pask [20] as well as the Myers-Briggs Type Indicator [3]. Most other learning style models classify learners into few types, whereas Felder and Silverman describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions using values between +11 and −11 for indicating the learners' preferences on each dimension. By using scales rather than types, the strengths of learning style preferences can be described, enabling the model to distinguish between strong and weak preferences for a particular learning style. FSLSM has often been used in research related to learning styles in advanced learning technologies. According to Carver et al. [4], 'the Felder Model is most appropriate for hypermedia courseware' (p. 34). Kuljis and Liu [15] confirmed this by conducting a comparison of learning style models with respect to their application in e-learning and Web-based learning systems. As a result, they also suggest FSLSM as one of the most appropriate model, arguing that it fits well for fulfilling the adaptability that tailors to learning differences and individual needs.

FSLSM characterizes each learner according to four dimensions: active/reflective, sensing/intuitive, visual/verbal and sequential/global. Active learners learn by trying things out and working together with others, whereas reflective learners learn by thinking things through and reflecting about them, and they prefer to learn alone.

Sensing learners like to learn from facts and concrete examples, tend to be more practical and are careful with details, whereas intuitive learners prefer to learn abstract material such as concepts and theories, like challenges and are more innovative. Visual learners remember best what they have seen, whereas verbal learners get more out of words, regardless of whether they are spoken or written. Sequential learners learn in linear steps, prefer to follow linear, stepwise paths and be guided through the learning process, whereas global learners learn in large leaps and prefer a higher degree of freedom in their learning process.

Felder and Soloman developed the Index of Learning Styles (ILS) [9, 10], which is a 44-item questionnaire for identifying learning styles based on the FSLSM. Several studies (e.g., [16] [32]) have investigated the reliability, validity and suitability of the ILS questionnaire to identify students' learning styles, concluding that the questionnaire may be considered as reliable, valid and suitable.

To consider learners' context in the proposed adaptive mobile system, sensor technology is used to retrieve valuable information about the learners' context and situation. In this research, we focus on four sensors and types of context information. The *proximity sensor* is used to detect the relative location of the device to the learner (e.g., whether the learner is talking on the phone). The *accelerometers* are used to detect the overall motion of the device. The *ambient light sensor* is used to detect the amount of ambient light in which the device is located (e.g., whether the device is used in a dark environment). The *GPS sensor* is used to detect the current geographical location of the device. All these sensors are commonly available in smartphones and interfaces are available to reliably retrieve the respective context information from these sensors.

The paper is structured as follows: The next section discusses related research works. Section 3 presents an in depth discussion of the system as a whole. The evaluation of the system is introduced in Section 4 and Section 5 discusses conclusions, limitations and future works.

2 Related works

There has been done a lot of research work in the field of adaptive hypermedia and many desktop-based adaptive learning systems have been developed and successfully evaluated. Taking a closer look at desktop-based learning systems that consider the different learning styles of students, examples of such systems include the two-source adaptive learning system (TSAL) [26], the web-based educational system with learning style adaptation (WELSA) [21] and an add-on to learning management systems such as Moodle [11]. The evaluation of these systems showed that considering learning styles can decrease learners' effort in terms of time required for learning and increase overall learner satisfaction. However, so far, only little research has been conducted on considering learning styles in mobile settings, supporting learners not only to learn anytime and anywhere, but also adjust the learning content and activities to students' preferred ways of learning.

In the mobile learning area, the recent advances in wireless telecommunication and the proliferation of ubiquitous mobile computing has resulted in significant growth of mobile learning during recent years [1]. As a consequence, mobile learning can take place at anytime and anywhere [27]. Although there were questions regarding the overall usefulness of early mobile devices for e-learning and the maturity of m-learning [28], technology has grown significantly since those early days. Today, learners can access computers and the internet thanks to personally owned mobile devices, outside the realm of the laptop [5].

One of the early works on adaptive mobile systems that influences our proposed system has been conducted by Jung, Park and Chung [13]. In 2006, Jung, Park and Chung presented a mobile learning system that provided contents in an adaptive manner based on a mobile learner's attributes [13]. However, in the six years since their work was released, the advance of technology has dramatically changed the field in terms of the possibilities, but the concept of portable mobile learning was still very much present at that time. Jung, Park and Chung's implementation involved web-based adaptivity, and the mobile device was used as a terminal. In contrast to our work, Jung, Park and Chung did not consider learning styles in their adaptation but other factors such as grades, available time and curriculum were used [13]. Tan, et al. [25] in 2009 described a location based framework for mobile learning. One of the noted concerns for the researchers was that the addition of any hardware that may be required by the mobile application would reduce the overall compactness of the device [25]. The current miniaturization of the smartphones has helped significantly reduce this concern. Therefore, it seems that technology is in part driving the research in this field, with increased device computational power and an ever decreasing technological footprint, advanced adaptivity and personalization in mobile computing research becomes possible.

Recently, adaptive mobile systems use this increased computational power and the availability of sensors in mobile phones to provide learners with personal context-aware support. An example of such a mobile, adaptive and context-aware system is proposed by Miso, Hornos & Rodriguez [18] involving geographical and cultural information based on one's locations [18]. In their work, Miso, Hornos & Rodriguez incorporate location awareness with personal preferences and provide users with information about cultural, training and leisure activities that they could probably be interested in via a context-aware recommender system [18]. In another example, Nguyen, Pham and Ho [19] propose the incorporation of adaptive mobile learning systems for language learning. Nguyen, Pham and Ho used context-awareness and adaptation within mobile learning to help in preparing students for the English proficiency test TOEFL [19]. However, our study differs from both of these examples in that our proposed system provides a platform for any type of course content, and is not limited to a single subject matter nor field of study.

Furthermore, there exist a few works that combine mobile learning and the consideration of learning styles. An example is the research prototype tool proposed by Razek and Bardesi [22] which considers students' learning styles based on the Anderson's learning style model [2]. However, although the system is for mobile devices, Razek & Bardesi did not considered contextual awareness.

Although the future of this type and usage of technology is promising, it is not without its fair share of challenges. Wu, Lee, Chang & Liang, [29] discussed the challenges faced by utilizing augmented reality in education. Like past innovations it is thought that augmented reality systems could encounter constraints and resistance from schools and teachers [29]. Santos, Hernández-Leo, & Blat, [23] discussed implications for geolocated mobile learning: the use of smartphones is changing the way of learning and teaching outdoors [23]. They argue for an integration into current educational curriculums in order to increase the impact of the outdoors activities in the learning outcomes in a diversity of subject matters [23]. Integration, acceptance and integration are points that any type of learning technology - including the one presented in this paper - must overcome.

3 System architecture

This section describes the architecture and respective components of the proposed adaptive mobile learning system. The system aims at considering the learning styles of students as well as their current context for selecting appropriate formats to present learning content.

Figure 1 illustrates the systems' architecture. In the subsequent subsections, the main components of the system are explained in more detail.

3.1 ILS questionnaire component

The Index of Learning Style (ILS) questionnaire [9] is comprised of a series of 44 questions created by Felder and Soloman to identify a user's learning styles based on FSLSM [7]. The ILS questionnaire component is responsible for administering the ILS questionnaire via the user's interface, and calculating the results for the user from his/her answers.

Typically, the results of the ILS questionnaire are four values between +11 and −11, mathematically representing the range from one end of the spectrum e.g. from 11a (+11) to the other end of spectrum e.g. 11b (−11) as was proposed by Felder and Soloman [8, 9]. Each range representing a learning style preference on one of the four dimensions of the FSLSM.

Due to internal calculation purposes, the ILS questionnaire component uses a different representation of the ILS results. Instead of the four values that represent learning style preferences on each dimension, eight learning style scores are used, each representing the learners' preference for one of the eight learning styles. They are as follows:

- ACT – Active Score
- REF – Reflective Score
- SNS – Sensing Score
- INT – Intuitive Score
- VIS – Visual Score
- VRB – Verbal Score
- SEQ – Sequential Score
- GLO – Global Score

Each score has a range from 0 to 11 and each score on the same dimension (e.g., active and reflective) is dependent on the respective other score, where the sum of both scores has to result in 11 (since there are 11 questions for each learning style dimension). For example, if ACT is 5, then REF is 6.

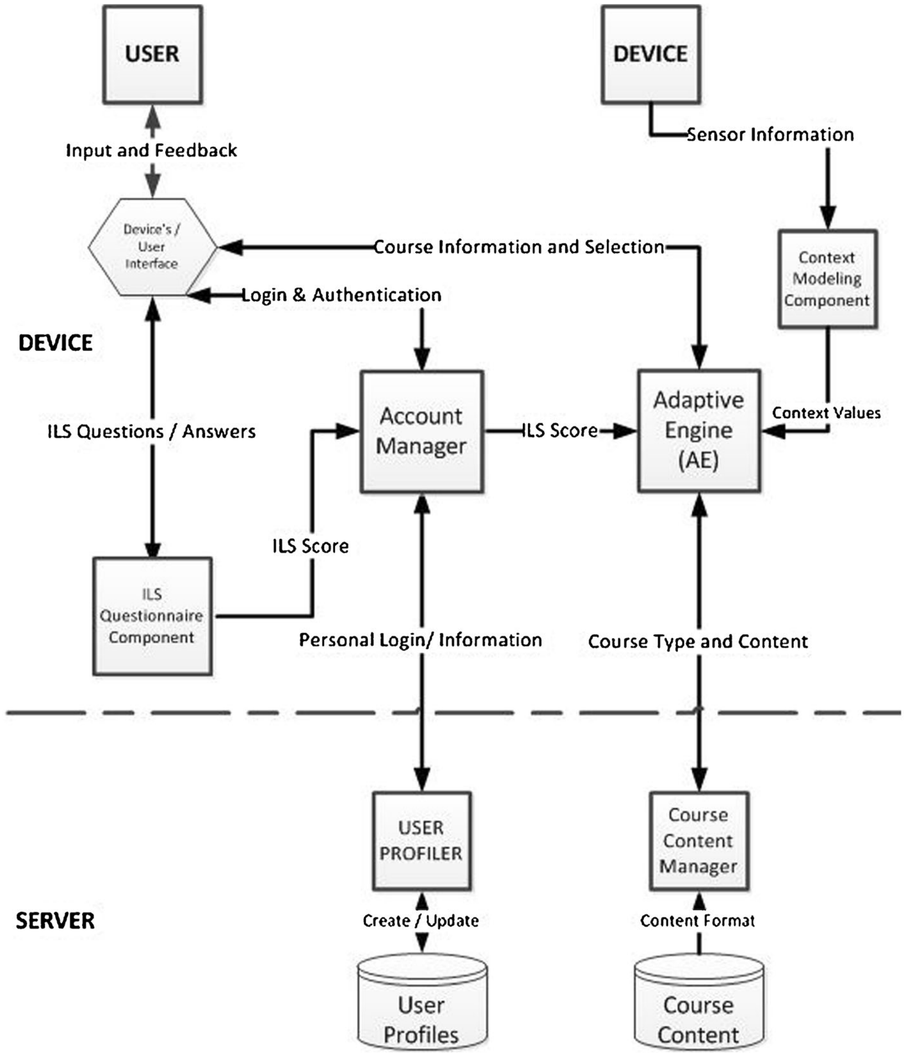

Fig. 1 System architecture

The scores are passed to the Account Manager and stored in the user's profile on a remote server. Furthermore, the Adaptive Engine uses these scores as input for determining an appropriate format for presenting the learning materials.

3.2 Account manager, user profiler, and user profiles database

While the Account Manager is responsible for managing the user profile on the device side, the User Profiler is responsible for managing and providing access to the user profile on the server side. The user profile includes details about the user, the user's learning style scores, login information, course completion information, and user-defined settings. This information is stored in the User Profiles database on a remote server. To access and store this information, the Account Manager communicates with the User Profiler which is then storing the respective information in the User Profiles database or accessing it from there respectively.

3.3 Context modelling component

The Context Modelling Component provides contextual information gathered from the devices' various sensors. At the current stage, this information includes data about the relative location of the device to the user gathered from a proximity sensor, the overall motion of the device gathered from an accelerometer, the amount of ambient light in which the device is located gathered from an ambient light sensor, and the current geographical location of the device gathered from a GPS sensor.

The gathered data is in a native format to the device. This raw data from the sensors is processed, and the results are stored on the mobile device within the Context Modelling Component for eventual usage in the Adaptive Engine.

3.4 Course content manager and course content database

In order to allow for the course to be adaptive to not only the student's particular learning style but also to changes with respect to the device's and user's context, every section of the course is available in four different formats: Audio (mp3), Video (mp4), Presentation (ppt) and Text-based (pdf).

The course material is stored on a remote server in the Course Content database and is accessed via the server-side Course Content Manager. The Course Content Manager is responsible for providing the course material in the requested format to the Adaptive Engine. Each section is divided in several segments. These segments include learning materials for about 1–2 min. Each segment could be played/viewed in an interchangeable sequence without the loss of course continuity, where the format is recommended according to the results from the Adaptive Engine.

3.5 Adaptive engine

The adaptive engine is responsible for the personalization of the courses by calculating the optimal delivery mode for course content. This calculation involves the users' learning styles, as determined in the ILS Questionnaire component as well as their current context, detected by the Context Modelling Component.

Once the appropriate delivery mode has been calculated, the Adaptive Engine contacts the server via the Course Content Manger in order to obtain the required content and then presents the respective content to the user.

In this section, the inner mechanics behind the Adaptive Engine are presented.

3.5.1 Determining course content format based on learning styles

Four different course content formats are considered in the adaptive mobile learning system. These formats are commonly used in educational settings and include audio, video, presentations and text-based format.

In order to determine which course content format is most appropriate for a learner with a particular learning style, for each course content format a respective score is calculated, representing the support level of the respective format for a learner with a particular learning style. Once these format scores are calculated by the adaptive engine, the format with the highest numerical score is then used to present the course content to the user. As each individual component of the ILS Questionnaire [8] has a possible range value of 0 to 11, then any calculation using a combination of those components will have values in multiples of 0 to 11, such as 0 to 22 (using two components) or 0 to 44 (using four components). Therefore, as each of the described formats (audio, video, presentations and text-based formats) are comprised of four components, each with a scale from 0 to 11, each of the described formats, will have an overall possible range value of 0 to 44.

Audio format The audio format is playing an audio file for the user, in a similar fashion to the popular books on tape. Based on the descriptions of the FSLSM [7], the characteristics of the audio format support a sequential, reflective, verbal and sensing learning style. A sequential learning style is supported since an audio file progresses in a linear fashion which facilitates linear steps for the learners which is one of the main characteristics of a sequential learning style. Since learners can pause the audio to reflect on contents as needed, an audio format also supports a reflective learning style. Furthermore, a verbal learning style is supported since the audio format is a recording of the spoken word, which again is highly preferred by verbal learners. Since the audio format is often factual and learners have to utilize their sense of directly absorbing information, the audio format also supports a sensing learning style.

The score for the audio format ($\text{AudioScore}_{\text{LS}}$) represents how well the audio format supports a learner with particular learning style preferences on a scale from 0 to 44. $\text{AudioScore}_{\text{LS}}$ is calculated as presented in formula (1).

$$\text{AudioScore}_{LS} = SEQ + REF + VRB + SNS \tag{1}$$

Video format The video format involves playing a video file for the user, which shows a video of the course as if the lecturer were being recorded in a lecture hall. Based on the descriptions of the FSLSM [7], the characteristics of the video format support an intuitive, global and visual learning style. While typically videos support a sensing learning style, the videos used in this setting are recordings of live lectures. As such, they deal with concepts and theories and require the user's ability to absorb information via internal processes such as memory, speculation and imagination. Therefore, these video recordings strongly support an intuitive learning style. Since in lectures and therefore also in these videos, lecturers tend not to be regimented and often veer off on tangents when they speak, such lectures are in stark contrast to sequential learning and support a more global learning style as such a trait would better suit a learning who has the ability to learn topics on a global all-encompassing scale. Finally, since a lecturer often involves engagement either with hand motion or pictures and drawing on a chalkboard etc., these videos also support a visual learning style.

The score for the video format (VideoScore_{LS}) represents how well the video format supports learners with particular learning style preferences on a scale from 0 to 44. The VideoScore_{LS} is calculated as presented in formula 2.

$$\text{VideoScore}_{LS} = (INT{*}2) + GLO + VIS \tag{2}$$

The intuitive learning style preference (INT) has been multiplied by 2 in formula 2 since video lectures provide a very strong support for intuitive learners.

Presentation format The presentation format can be described as a Microsoft PowerPoint style format, including point-form based notes that could incorporate various other multimedia formats (video and audio). Furthermore, the progression of the format is user controlled. Based on the descriptions of the FSLSM [7], the characteristics of the presentation format support a sensing, global, active and verbal learning style. Since the presentation format facilitates the presentation of facts and hands-on activities, for example through animations, this format supports learners with a sensing learning style. Learners with a global learning style enjoy seeing the "big picture" and not microscopic details of the presentation. This is often true in the bullet or point form nature of the presentation/power point style format. Additionally, due to the inclusion of multimedia elements in the presentations, learners no longer need to go through the presentation in a sequential way but can select between media elements, which provides learners more freedom in how they learn and again supports a global learning style. Furthermore, through these media elements, learners can engage and interact with the presentation (e.g., animations), which supports an active learning style. As the majority of the content of this presentation format is still about reading and hearing recorded voice, the video format supports learners with a verbal learning style.

The score for the presentation format ($\text{PresentationScore}_{LS}$) represents how well the presentation format supports a learner with particular learning style preferences on a scale from 0 to 44. The $\text{PresentationScore}_{LS}$ is calculated as presented in formula 3.

$$\text{PresentationScore}_{LS} = SNS + GLO + ACT + VRB \tag{3}$$

Text-based format The text-based format is a written version of the course, similar to what would be presented in a textbook, including diagrams, figures and other visual aids. Based on the descriptions of the FSLSM [7], the characteristics of the text-based format support a sensing, sequential, reflective and visual learning style. The text-based format supports a sensing learning style since it provides the learners with facts and details as well as facilitates the user's ability to absorb information via his/her visual sense, for example when presented with pictures, diagrams, etc. Since learners are expected to go through the text-based format in a sequential way, this format supports a sequential learning style. Furthermore, since reading tends to be a solitary, highly reflective and introspective experience, the text-based format also supports a reflective learning style. Finally, since the text-format also includes graphics, diagrams, pictures, etc., this format also supports a visual learning style.

The score for the text-based format (TextScore_{LS}) represents how well the text-based format supports a learner with particular learning style preferences on a scale from 0 to 44. The TextScore_{LS} is calculated as presented in formula 4.

$$\text{TextScore}_{LS} = SNS + SEQ + REF + VIS \tag{4}$$

3.5.2 Determining course content format based on context and learning styles

A user's learning style may not be the only factor in determining a particular course content format. The context and surroundings in which the device and user are located, provides additional factors to consider when determining the optional course format. Today, mobile phones are equipped with many sensors which can gather information about their environment and surroundings. These sensors can be used to identify the user's motion, location, activities and needs, which in turn can affect the optimal course content format beyond one's learning style.

The sensors considered in this adaptive mobile learning system represent those found in the majority of smartphones currently on the market. In the subsequent sections, we present how data from these commonly used sensors provide context information that can affect the preferred course content format and can trigger recommendations for a different format.

Since the raw sensor data varies by each device depending on the manufacturer's specifications, a constant Cs is introduced for each sensor, where s denotes the respective sensor. This constant is introduced in order to help normalize the sensor data across a multitude of devices. These constants aim at balancing the effect of learning styles and context information as well as the effects of different manufacturers.

Proximity sensor The proximity sensor is used to detect how close the device is to the user. The sensor data from the proximity sensors is commonly represented by the device in a Boolean value, a 1 or 0 for either in close proximity or not. If the proximity sensor is active (i.e. a close proximity has been detected), it means viewing the screen is not possible, hence the system should default to the audio format as the optimal course content format.

Accelerometers An accelerometer on the device detects the overall motion of the device. An increase in the device's motion is considered as less favourable towards a printed media format since the user is, for example, walking, running or going by bus.

In order to calculate the movement of the device (*mov*), all three axis (x, y, and z) are considered. In Formula 5, the movement (mov) represents the average acceleration, calculated along the 3 axis, X-axis, Y-axis and Z-axis. Although the specific axis of the movement is not important, the overall acceleration is of interest, thus the equally weighted average of the accelerations in each axis. In Formula 5, the average of all movement across all three axes is calculated and then, multiplied by a constant C_{acc} to normalize the result to a scale of 0 to 22. This is done in order to obtain a scale that commences at a 0 value, instead of having the scale range from −11 to +11.This scale ensures that the effect of learning styles and the effect of context information are equally weighted for determining the optimal course content format. The scale is derived in the following way: While the format scores calculated based on learning styles (i.e., $AudioScore_{LS}$, $VideoScore_{LS}$, $PresentationScore_{LS}$, $TextScore_{LS}$,) have a scale of 0 to 44, the scale for context information should also be from 0 to 44, so that learning styles and context information have equal effects. Since there are two sensors (the accelerometer and the ambient light sensor) that provide context information which influences the calculation of the optimal course content format based on learning styles and context information, the scale for each of these two sensors should be from 0 to 22, leading to a scale of 0 to 44 for both of them.

$$mov = \left((\text{averageAccelX}*C_{acc}) + (\text{averageAccelY}*C_{acc}) + (\text{averageAccelZ}*C_{acc}))/3\right) \quad (5)$$

As movement of the device favours audio format and hinders visual formats, the score of the audio format increases with detected movement, while the score for the video, presentation, and text format decrease the more movement is detected. The score for video format is not affected as much in contrast to the score for text and presentation format, since it is much harder to read text than it is to watch a video of a presenter when the screen is moving. Therefore, the score for the video format is only decreased by a factor of one half of the movement. Formulas 6, 7, 8, and 9 show how the format scores are calculated when considering learning styles and movement.

$$\text{AudioScore} = \text{AudioScore}_{LS} + mov \quad (6)$$

$$\text{VideoScore} = \text{VideoScore}_{LS} - (mov/2) \quad (7)$$

$$\text{PresentationScore} = \text{PresentationScore}_{LS} – mov \quad (8)$$

$$\text{TextScore} = \text{TextScore}_{LS} – mov \quad (9)$$

Ambient light sensor The ambient light sensor detects the amount of ambient light in which the device is located. Such information can affect the course content format in that a very bright or dark local environment favours the audio format rather than a text, video or presentation format.

The value for ambient light (*al*) is taken directly from the mobile device's sensor as raw data. Ambient light sensors usually produce a value of near zero for darkness and increase in value the greater the lux. Since both, a dark and bright environment are not optimal conditions, a *midwayPoint* is defined, which represents such optimal condition. Therefore, as per formula 10, the deviation from the midway point is considered for calculating the value for ambient light (*al*). The value for ambient light is on a scale of 0 to 22, where 0 represents an optimal light condition and 22 represents poor light condition, either due to darkness or very bright light. Similarly to the movement calculated in the previous section, a constant $C_{als}$is used to normalize the ambient light value to the scale of 0 to 22. This scale ensures that the value for ambient light has the appropriate weight in relation to the learning style scores.

$$al = \left| \left((\text{valueOfAmbientLightSensor} - \text{midwayPoint}) * C_{als} \right) \right| \tag{10}$$

Since text, video and presentations are difficult to see in very bright and dark environments, the score of the text, video and presentation format decreases the poorer the light condition becomes. As very bright or dark environments favour an audio format, the score of audio format increases with a poor light condition. Formulas 11, 12, 13 and 14 show how the format scores are calculated when considering learning styles and ambient light.

$$\text{AudioScore} = \text{AudioScore}_{LS} + al \tag{11}$$

$$\text{VideoScore} = \text{VideoScore}_{LS} – al \tag{12}$$

$$\text{PresentationScore} = \text{PresentationScore}_{LS} – al \tag{13}$$

$$\text{TextScore} = \text{TextScore}_{LS} – al \tag{14}$$

GPS sensor The GPS sensor is able to read the position of the device in terms of its geographical location and returns the longitudinal and latitudinal coordinates. With the ability to set pre-determined locations, a user is able to manually set a particular course content format for a given location/set of coordinates. For example in a library, the course content format may be defaulted to always present in a text format. The user may add/edit/delete these locations and their respective course content format at any time. Once a location is added, the GPS coordinates are stored on the device as well as on the server as part of the user's profile, together with a user-defined radius for the location.

By allowing the user to manually set a particular course content format depending on the location, the user is able to disregard the effect of learning styles and other context information entirely and use the course content format that has been defined at the respective location.

In order to determine whether the user is in a predefined location, the GPS coordinates are compared with the stored locations of the user and a Boolean score is returned, indicating that either the device is or is not in a user's pre-defined area.

Combining context and learning style information While the proximity sensor and the GPS sensor default the course content format to a particular format, the other two sensors (accelerometer and ambient light sensor) provide context information that affects the optimal course content format and lead to a calculation of the optimal format based on learning styles and context information. Formulas 15, 16, 17, and 18 describe how to calculate each format score based on the format scores calculated from learning styles (as described in Section 3.5.1) and context information, gathered from the accelerometer and ambient light sensors. The format score that yields the highest value is recommended for content delivery.

$$\text{AudioScore} = \text{AudioScore}_{LS} + mov + al \tag{15}$$

$$\text{VideoScore} = \text{VideoScore}_{LS} – (mov/2) – al \tag{16}$$

$$\text{PresentationScore} = \text{PresentationScore}_{LS} – mov – (al/2) \tag{17}$$

$$\text{TextScore} = \text{TextScore}_{LS} – mov – al \tag{18}$$

4 Evaluation

In order to evaluate the system, an application for iOS was implemented, designed to run on the iPhone platform, and a pilot study with 45 participants has been conducted. This pilot study only used the learning style adaptation and did not consider context due to the limitations of the iOS simulator. This section discusses the materials used for the course creation, the data of the study as well as the research methodology and results.

4.1 Materials

A course was created to cover basic astronomical principles. The course covered typical content found in most high school senior year Earth Science classes – similar to a typical science television show on astronomy.

The course is divided into six sections, with the first and last sections being the introduction and conclusion. The remaining sections covered such topics as the sun and stars, planets, comets and meteors, and more esoteric astronomical concepts such as wormholes and black holes. Each section contained approximately six factual points of interest that would be valid in a test/quiz. In addition there were about twenty other testable items of information that may or may not have been common knowledge. The course is expected to last approximately 15–25 min.

There were three main course content formats used for this study: Audio, Video and Text. The presentation format was not used in the iOS test application, since there is no native support for a presentation or PowerPoint format. The six sections were divided into overall 15 segments where each segment included course content to be learnt in about 1–2 min. Each of the 15 segments was recorded/presented in the three formats. This allows for the course to switch between formats as needed without the loss of continuity to the user. The audio format was simply a commonly used and familiar MP3 format audio file using a standard audio player interface. The textual format was a PDF file (see Fig. 2), and the video format was a video of a presenter giving a lecture (see Fig. 3).

4.2 Data

In total 45 students participated in the study. All the students were volunteers obtained from the entire student body in grades 11 and grades 12 within a public high school in

COMETS

What are they?
How are they formed?
What are they made of?
What's in a tail anyway?

A comet, is a ball of rock and ice (often called a dirty snowball). They are made up of the debris left over from when the planets were formed. They are in orbit around the sun, in very long and elliptical orbits raning from a few years (under 100yr orbits) to tens of thousands, and some that never return.
When the ball gets close enough to the sun, the sun's rays (called solar wind) melt the outside of the comet, this melted comet material flies off the central chuck to form what is known as a tail or coma. Comets are really then just leftover building blocks of the solar system. There are

Fig. 2 Text Format

Canada. The selection of the senior grades of the school, assured that any students who volunteered would provide a population sample that were familiar with the usage of computers, yet were not necessarily already familiar with the test's subject matter of astronomy. As such, it is hoped they may pose a suitable representation of Canadian high school students as a whole.

In order to maintain the anonymity of the students, each student was assigned a value *S*, ranging from 1 to 45. So the first student was assigned the value S1 and the last student S45. This was done to ensure that the pre-test and post-test were properly associated with one another. Out of the 45 participants every student stayed for the

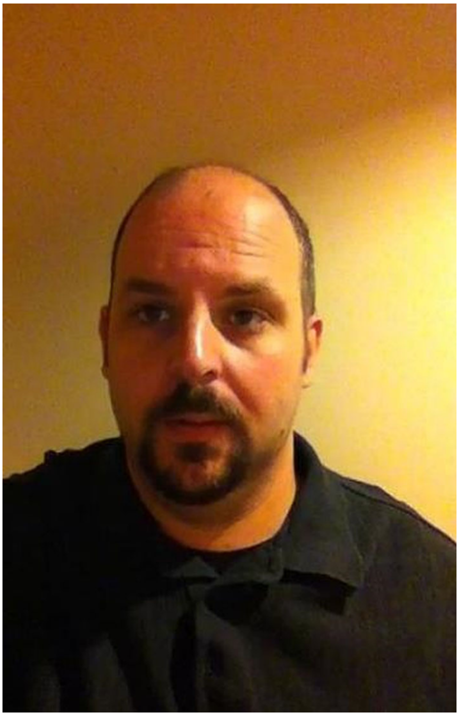

Fig. 3 Video format

duration of the study and completed both tests. The tests were done on paper and marked by hand. No information was retained on the application.

4.3 Research methodology

The aim of the evaluation has been to investigate the effectiveness of the system in supporting students' learning as well as the systems' user-friendliness.

In order to gauge the effectiveness in supporting students' learning, a series of two quizzes (pre-test and post-test) have been administered. The two tests were designed to determine the students' knowledge of astronomy before and after they have used the system. The pre-test and post-test quizzes consist of the same set of 20 questions on basic astronomical principles, in different order. All questions posed in the quizzes were covered as content/material within the course. Students do not receive feedback about whether a question was answered correctly or not after the pre-test. Therefore, it is also possible that students' scores on the post-test are equal to their pre-test scores or even decrease.

At the beginning of each student's participation, the student takes the initial 20-question pre-test quiz. The students have no or little prior knowledge of the subject matter, thus the pre-test attempts to demonstrate the students' understanding level of the subject matter prior to the usage of the adaptive learning system application. Immediately after completing the pre-test quiz, the students then use the adaptive learning system for the duration of the course – depending on student speed and course content format, from 15 to 25 min. Once completed the adaptive course, the students then take the post-test.

In order to statistically analyse the effectiveness of the system in increasing students' knowledge on the subject matter, both pre-test scores and post-test scores are analysed for normal distribution, using the Kolmogorov-Smirnov test. If the Kolmogorov–Smirnov test indicates a normal distribution, a paired t-test is performed in order to find out whether there is a significant difference between the pre-test scores and the post-tests scores. However, if the Kolmogorov–Smirnov test shows that the data does not follow a normal distribution, instead of a paired t-test, a Wilcoxon test is preformed to determine the difference between the pre and post–tests.

In order to determine the user friendliness of the system, each student was given a feedback survey to gauge their acceptance and attitude towards the adaptive system. This feedback survey was administered at the end of each student's participation, i.e. after the post-test was taken. The feedback survey is comprised of a series of five questions. The students' responses were on a scale from 1 to 10. In the case for all five questions, the lowest value of 1 indicated that the student strongly disagrees whereas the top value of 10 indicated that the student strongly agrees with the statement in the question. The questions are as follows:

1) I enjoyed using this application.
2) I found this way of learning suited my needs.
3) I would use this again.
4) I would suggest this type of application to a friend.
5) I would like more courses to be offered in this fashion.

4.4 Results & discussion

This section presents the results of the study as well as a discussion on these results.

For the pre-test, the mean and median score for all 45 students participating in the study were both 13 (out of 20), with a standard deviation of 3. For the post-test, results showed a mean score of 16 (out of 20), with a standard deviation of 3, and a median of 17 (out of 20). Since the average score obtained in the pre-test was 13 (out of 20) and the average score in the post-test was 16 (out of 20), the improvement was on average 3 marks out of 20. These 3 marks represent an improvement of approximately 23 % of the pre-test quiz score.

As a result of the Kolmogorov-Smirnov test, both pre-test and post-test scores are normal distributed using a significance level of 0.05 (pre-test: $p = 0.801$; post-test: $p = 0.076$). Therefore, a two-tailed t-test was conducted. The results of this t-test demonstrate a strongly significant difference between the pre-test and post-test scores ($p < 0.001$), using a significance level of 0.05. By conventional statistical criteria, this difference is considered to be extremely statistically significant.

As the quizzes were collected (along with the user feedback survey) and were marked off-site, this assured that any improvement in the score was likely due to information obtained/learnt from the adaptive course. As the student did not know if their responses to their first quiz were correct or not, they would not have been able to adjust their answers for the second quiz accordingly. Thus, any changes that are made can be attributed to either random guessing, cheating or from information obtained from the adaptive application. As the students were all under constant supervision, and they were aware their results were anonymous and could not affect their scholastic grade, cheating can be ruled out as a possible source for error. Furthermore, the strongly significant difference between the pre-tests scores and post-test scores makes random guessing as a factor in the students' increased scores very unlikely, and therefore, the change in students' scores from pre-test to post-test can be attributed to the actual increase of knowledge gained from the adaptive course.

Although such an improvement is quite telling in terms of the effectiveness of the adaptive system, the user survey was even more revealing (Table 1).

Out of the 45 students, 3 students choose not to respond in the user feedback on the system. As can be seen from Table 1, students provided very positive feedback on the application. The feedback shows that students enjoyed learning with the adaptive system (median of 7 out of 10), the content format suited their needs (median of 8 out of 10), they would use the application again (median of 8 out of 10), they would suggest the adaptive system to a friend (median of 7 out of 10) and they wished to have further classes in this fashion (median of 9 out of 10).

It is interesting to note that question 1 and question 5 of the feedback are asking in fact a similar question, however there is an obvious difference in response. When asked if they enjoyed using the application in question 1, students may have associated their response to the rather technical subject matter of the course content presented – not the overall content delivery and adaptive functionality. For when asked if they wanted more courses in this fashion, their score had a median value of a 9 out of a possible 10 - the highest score in the entire feedback survey. The same can be attributed to the lower score about recommending this type of course to a friend. It received the same value as question 1, which was a score of 7 out of 10. Here again, it is thought that the students

Table 1 User feedback survey

	Median Result
Question 1	7
Question 2	8
Question 3	8
Question 4	7
Question 5	9

may have interpreted the question as appertaining to the course subject matter rather than the course content delivery style and the adaptive system itself.

5 Conclusions

In this paper, we propose a system for considering students' learning styles and context information in order to provide them with personalized content in mobile settings. The overall results were promising in showing a 23 % improvement in subject matter understanding and an overall high acceptance for not only the application, but also the personalized course format. In a society that is becoming ever more synonymous with 24/7 connectivity, the ability to effectively incorporate learning into the mobile social framework of our youth is a very powerful learning tool.

This paper demonstrates the theory and application of combining information about the learners with context information in order to provide them with adaptive learning through their mobile devices. The students who participated in our study have expressed a strong willingness to seek further courses offered in this adaptive format. The findings show that not only does the application of an adaptive mobile learning environment succeed in supporting students' learning, but also that the system is user friendly. With the strong difference between the pre-test and post-test results, and the very positive feedback from the survey, the proposed system seems very promising in supporting students' learning. From an educational standpoint, the mobile aspect frees them from the confines of a traditional classroom and students are able to learn not only on their own time, but also wherever they choose to learn, while getting presented with adaptive learning contents. Although these results are specific to the population tested, it is hoped that further work of this nature will reinforces the findings presented in this study.

Due to anonymity required for testing the system with students, no user specific data was stored on the application - thus each time the user wished to use the system, they would need to re-take the ILS questionnaire. This had no negative effect on the study since every student used the application for only one learning session and therefore, had to fill out the ILS questionnaire only once. Furthermore, for testing purposes, as the students were utilizing iOS simulators, the various context awareness pieces of the application were not available, and thus not utilized.

Although very telling in terms of the adaptive engine, the contextual adaptivity of the system was not evaluated in this study. Future work will certainly move towards allowing for a broader usage of the application on mobile devices and evaluating the context-awareness part of the system. At present, there has been interest from educational institutions to utilize a refined application that considers learning styles and context information within the standard high school curriculum. This would certainly allow for potentially thousands of students using the system.

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