Context-Aware Adaptive M-Learning: Implicit Indicators of Learning Performance, Perceived Usefulness, and Willingness to Use

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ABSTRACT
Mobile learning tools can enable high-quality education on a large scale at low costs. However, these tools also suffer from low engagement, and they lack content personalization and adaptation. Therefore, research on meeting the diverse needs that are imposed by devices, users, usage contexts, and infrastructure variations are increasingly important. This pilot study investigates how learning performance is affected by perceived usefulness and the willingness of undergraduate students to use an adaptive m-learning tool that personalizes the learning materials' format to the user and device contexts. An assessment was done using an implicit measure (dwell time), an explicit measure (satisfaction questionnaire), and a learning assessment (post-test). An experiment was conducted with convenient sample of 31 students; approximately half of the students used a traditional school e-learning system, and the other half used the context-aware adaptive learning tool. The study used implicit and explicit indicators to empirically validate a score-based model that calculates the scores for different learning material formats based on the user and device contexts. The results suggest that context-based adaptive mobile-learning tools can significantly improve the perceived usefulness of learning materials, as well as learners' willingness to use the tools. Practical and theoretical implications were suggested for the design of context-aware adaptive mobile-learning tools to assess and enhance learners' perceived usefulness and willingness to use learning materials.

Keywords: Distance education and tele-learning; evaluation methodologies; human-computer interface; multimedia/hypermedia systems; secondary education.

INTRODUCTION
Recent advances in mobile technologies have opened the door to new learning environments. Mobile learning (m-learning) is changing the landscape of how people learn by providing learners with control over *when* and *where* they learn. Major e-learning providers, such as Coursera, edX, Udacity, and Khan Academy, have recently released mobile applications to offer *on-the-go* learning experiences (Pham et al., 2016). However, m-learning has also posed new challenges due to the lack of personalization. Such challenges are caused by variations in mobile device technologies, unstable wireless network connections, media formats, and changing learning contexts due to users' mobility (Sahid et al., 2018). M-learning is expected to provide more adaptive services in accordance with the changing learning context by adopting context-aware adaptive content approaches (Sahid et al., 2018).

Recent research on context-aware adaptive m-learning systems seeks to provide the most appropriate learning settings for each particular learner. Context-aware systems gather information about the users, their surroundings, and their mobile device capabilities. These contextual data are used to adapt learning materials to the context of its execution according to users' needs and equipment. The ultimate aim of a context-aware adaptive m-learning system is to improve the learners' performance and satisfaction (Pham et al., 2016). Thus, explicit (such as self-reported data) and implicit (such as dwell time and mouse clicks) users' preferences are collected to dynamically personalize the learning contents (Garcia-Cabot et al., 2015).

This paper aims to provide learners with an adapted course content format based on their contexts. The suggested model provides learners with an adapted course content format (audio, video, text, and presentation) based on their preferences (user context), and based on their mobile battery and connectivity conditions (device context). This adaptation is made by calculating scores for each content format; the format with the highest score is then delivered to the learner. An empirical assessment of the effects of the context-aware adaptive material on learning performance, perceived usefulness, and willingness to use was conducted.

2. BACKGROUND AND MOTIVATION

2.1 Context Variation in Mobile Learning

The conception of context has been recently acknowledged as a key factor in the design of mobile information systems in general and mobile learning systems in specific (Louhab et al., 2018). Various previous models assumed that the m-learning context of use can vary significantly and that learning performance can be improved by providing personalized and adapted learning content (Louhab et al., 2018). Sahid et al. (2018) divided m-learning contexts into four categories: internal, external, learning and interaction contexts. The internal learner context is related to users' characteristics (background, culture, language, preferences, and learning style). The external learner context is associated with users' surrounding physical environment (brightness, noise, device capabilities, Internet connectivity, location, and time). The learning context reflects the learning skills and materials type, and the interaction context is mainly concerned with users' attitudes towards the system (Sahid et al., 2018).

Most early work on adaptive m-learning focused on the variations in external physical environments, such as time (Zhao et al., 2008), location (Gasparini et al., 2010), and Internet connection quality (Pachler et al., 2009). These studies assessed users' surrounding environments using sensors, and provide recommendations for personalized m-learning contents accordingly. Later research considered mobile device technology and learners' preferences by employing a mixture of more advanced techniques to assess the contexts' variation, such as data mining, learning analytics, log systems, and a user perception survey (Garcia-Cabot et al., 2015). In later research, learners' browsing behaviors were assessed to adaptively suggest the optimal format of learning materials (Pham et al., 2016). More recent research focused on the psychological states of the learners, including anxiety and boredom, which were naturally measured during interactions with the m-learning system, and learning materials were adapted accordingly (Sahid et al., 2018).

2.2 Context-Aware Adaptive Mobile Learning Models

Two notable models have been proposed for mobile learning content adaptation: static adaptation, which stores different versions of the content for users to select; and dynamic adaptation, which conducts real-time processing to adapt the content based on users' requests, environmental context, and mobile device capabilities (Louhab et al., 2018).

An example of the Static Adaptation of mobile learning content is the SECA-FML (Smart Enhanced Context-Aware for Flipped Mobile Learning) approach that was proposed by Louhab et al. (2018).

The suggested approach takes into account three context parameters: the software that is installed on the mobile device, the mobile device capabilities (screen size, resolution, and battery), and the Internet connectivity. Based on the calculation of the acquired context parameters, scores were calculated for each pre-installed format, and the format with the highest score was selected. Another static adaptation model was proposed by Bicans et al. (2017); this model assesses the users' learning style and selects the content format from a predefined set of learning materials to provide the necessary level of support for a particular learning style.

An example of the dynamic adaptation of mobile learning content is the personalized learning content adaptation model (PLCAM), which was suggested by Su et al. (2011). The model addresses the limitations of mobile learning in terms of device constraints (size, memory visualization, and bandwidth). The model used the historical server logs of mobile devices' capabilities, learners' preferences, and network conditions to provide adaptable learning content. The PLCAM utilized data mining techniques to manage a large number of similar previous learners' requests. The model dynamically made adaptation decisions and provided suitable versions of the learning content.

2.3 Implicit Indicators of Mobile Content Usefulness

With the vast growth of the amount of educational materials on the Internet and e-learning systems, finding relevant and useful materials is becoming a real challenge for e-learners. Intensive e-learning studies are looking to enhance the perceived content usefulness based on learners' explicit and implicit feedback. To save learners' time and efforts and gather a large amount of data with no costs, implicit feedback (captured via recording software while users perform specific tasks on computers) is currently widely use to capture learners' behaviors towards e-learning content (Pham et al., 2016). The dwell time, representing the accumulated time that is spent by a learner on an active document, is one of the most extensively studied implicit indicators and was suggested to be a reliable measure for document's usefulness (Kelly, 2004).

Lately, dwell time has been extensively used to reflect users' interest in a document and users' perception of documents' usefulness. Sluis et al. (2016) studied the relationships between learning materials' comprehensibility and two aspects of learners' behavior: the dwelling time (how much time students spend on learning material) and the dwelling rate (how much of the material they actually complete). D'Mello et al. (2012) used an eye tracker system to monitor students' gaze patterns, aiming to improve learning by dynamically detecting and responding to students' disengagement. The study evaluated the efficacy of eye tracking at promoting learning engagement in a controlled experiment with 48 students. The results suggested that gaze-reactivity was effective at promoting learning gains.

2.4 Tablet-Based Learning in the Egyptian Education System

Equity and access to quality education are crucial issues in developing countries, especially with booming populations and significant shortages of classrooms, laboratories, and infrastructure. In this context, the potential benefits of E-Learning are particularly effective, and E-learning can be an alternative technique to provide the growing population with quality and accessible educational materials. Egypt has the largest education system in the Middle East and North Africa region with 20 million students in K-12 education, more than 46,000 public schools and almost one million public school teachers (UNESCO, 2018). According to the UNESCO Global Education Monitoring Report (2016), the current Egyptian education system (referred to as "EDU 1.0") is not delivering the necessary learning outcomes, skills, and competencies for further education and transition to the job market (UNESCO, 2018).

In September 2018, Egypt embarked on an education reform movement by launching a new education system (referred to as "EDU 2.0"). A fundamental element of this educational reform is the use of ICT and the establishment of digital infrastructure at the school level. The World Bank is funding the digital component of the Egyptian EDU 2.0, including the following: the digital content, a tablet per student, and a portable device per teacher. This initiative includes an expanded use of E-Learning resources, aiming to gradually shift from textbooks to digital learning resources. This shift represents a significant transformation in how students learn in the Egyptian schools, which needs to be studied.

2.5 Motivation

As illustrated in the literature review above, limited studies on context-aware adaptive mobile learning have examined learners' perceived usefulness and willingness to use adaptive learning materials, as well as the educational benefits of adaptation (Garcia-Cabot et al., 2015). Very few of these studies have empirically assessed the impact of context-based adaptive systems in terms of learners' perceived effectiveness and their willingness to use these systems using an experiential real case environment with implicit indicators. Moreover, few studies have considered the educational context of developing countries (Sahid et al., 2018).

This research is based on an experiential method where students from an Egyptian school are introduced to different versions of their school's e-learning systems, and then asked to perform predefined tasks in class and at home. Explicit and implicit indicators were collected during the students' interaction with the systems, and, after a usage period at the students' home, were used to assess the educational benefits and attitudes towards the m-learning system. Assessments were conducted in the students' actual school during their school hours using real curriculum information and systems. This *real world* setting would ensure an authentic reaction of students towards the m-learning-based education tools.

Based on the above discussion, the current study investigated the following Research Questions (RQ) about whether or not the learning performance of students is affected by adaptive mobile learning.

RQ1: Does adaptive mobile learning affect learning performance?
RQ2: Does it affect the learning materials' perceived usefulness?
RQ3: Are students willing to use the adaptive mobile learning tool?

3. RESEARCH METHODOLOGY

The current study hypothesizes that an adaptive tool that personalizes mobile learning materials to the user context and device context would positively affect learners' learning performance, perceived usefulness and willingness to use the system. The independent research constructs are the following: 1) adaptive materials (*adapt*: adaptive versus non-adaptive e-learning), 2) device context (*device*: device connectivity and battery conditions), and 3) user context (*user*: user preferred format). The dependent research constructs are the following: 1) learning performance (*learn*: participant scores in post-tests), 2) perceived usefulness (*p usefulness*: measured using an explicit rating & an implicit indicator of dwell time, and *dwell*: accumulated time in seconds spent by a user on an active learning material), and (3) willingness to use (*use:* user intention to use the system).

This section describes the experimental design and data collection tools to test the hypothetical research model.

3.1 Research Approach:

The study suggests an adaptive m-learning tool that provides learners with materials that are tailored to the user context and device context. The tool takes into account preset learner parameters (learners' preferences for material formats, preferred learning language, and self-reported knowledge level of the learned topic), as well as dynamic environmental parameters (mobile devices' connectivity and battery conditions), as follows.

User Context: -learner format preferences (PDF/ Power Point/ MP3 Audio/ MP4 Video)
-learner language preferences (Arabic/ English)
-learner self-reported knowledge level on a topic (Low/ Intermediate/ high)

Device Context: -system assessment of connectivity (limited/ unlimited Internet connection)
-system assessment of battery charge %

The selection of the material language and level is based totally on the learners' set preferences, while the selection of the material format is done by calculating the scores for each format and then selecting the format with the highest score to present the course material (Tortorella et al., 2015; Loubah et al., 2018a). The scores are calculated as follows.

First: The adaptive tool assigns a score of 1 or 0 to each available material format ($TextScore_{User}$/ $PresentationScore_{User}$/ $AudioScore_{User}$/ $VideoScore_{User}$) based on the users' preset preferences. A score is set to 1 if the learner selects it as a preferred format and 0 if not. Learners can select one or many preferred formats.

Second: The connectivity score ($connect_{Device}$) is calculated based on Loubah et al.'s (2018a) equation, where *connect* = 1 in the case of a limited connection and $connect_{Device}$ = 11 in the case of an unlimited connection. Since video consumes the most Internet connectivity, the video score decreases when a limited connection is detected. Audio consumes less connectivity than video but more than presentation and text, and the text and presentation formats need less Internet connectivity. Accordingly, the final format scores are calculated as follows after considering the *connect* score (Loubah et al., 2018a):

$$TextScore_{final} = TextScore_{User} + connect_{Device}$$
$$PresentationScore_{final} = PresentationScore_{User} + connect_{Device}$$
$$AudioScore_{final} = AudioScore_{User} - (connect_{Device}/2)$$
$$VideoScore_{final} = VideoScore_{User} - connect_{Device}$$

Third: The Battery score ($battery_{Device}$) is calculated based on Loubah et al.'s (2018a) equation, where *battery* = the percentage % remaining of the tablet's battery charge. Since video consumes the most battery energy, the video score decreases when a low battery is detected. Audio consumes less battery than video but more than the presentation and text formats, and the text and presentation formats consume less battery power. Accordingly, the final format scores are calculated as follows after considering the $battery_{Device}$ score (Loubah et al., 2018a):

$TextScore_{final} = TextScore_{User} + connect_{Device} + battery_{Device}$
$PresentationScore_{final} = PresentationScore_{User} + connect_{Device} + battery_{Device}$
$AudioScore_{final} = AudioScore_{User} - (connect_{Device}/2) - (battery_{Device}/2)$
$VideoScore_{final} = VideoScore_{User} - connect_{Device} - battery_{Device}$

Fourth: By adding the device parameter, the format final scores will be calculated as follows:
$TextScore_{final} = TextScore_{User} + battery + connect$
$PresentationScore_{final} = PresentationScore_{User} + battery + connect$
$AudioScore_{final} = AudioScore_{User} - (battery/2) - (connect/2)$
$VideoScore_{final} = VideoScore_{User} - battery - connect$

Finally: The format with the highest score is used to present the course material. If the scores are equal, the adaptive system will consider the users' format preferences.

3.2 Sample:

A convenience sample of thirty-one school students who were enrolled in grade 11 in a private school in Cairo participated in the experiment. Participant recruitment was conducted through open calls via the school's paper bulletin board at the entrance of the school. Students volunteered to take part in the experiment with no monetary compensation. A certificate of appreciation for the participants was put on the honor bulletin board at the school's entrance, and a thank you letter was handed to participants after the completion of the experiment. Participant ages ranged between 15 and 16 years old and 65% were females. All participants were familiar with the school's electronic learning tool (Moodle), and started to use it in grade 4. Additionally, all participants were familiar with using the school's tablets. Participants' proficiency with electronic learning skills was self-reported as between intermediate and high. Participants were divided into two groups. The experimental group consisted of 16 participants, and the control group included 15 participants. The control group learners were asked to use the non-adaptive e-learning materials, while the experimental group was asked to use the adaptive mobile-learning tool. Participants were given the option to join the experimental group.

3.3 Learning Material:

The learning materials were selected for participants' following year's (grade 12) study plan. The selected course was meant to be suitable for all participants' academic levels since they were supposed to study it in the following grade (grade 12); nevertheless, the topic is unfamiliar to all students to avoid any effects from participants' previous knowledge. Material on the "history of music" was selected and installed on the school's e-learning Moodle in two languages (Arabic/ English), on three knowledge levels (low/ intermediate/ high) and in four formats (PDF, Power Point, MP3 Audio, and MP4 Video). Participants were given the tablets to study the course at home for a week. To assess the effect of the adaptive tool, participants in the control group were introduced to the traditional non-adaptive system where they manually selected the material format. Meanwhile, participants in the experimental group were introduced to the adaptive tool where they were required to create an account and set their preferences prior to logging into the tool.

3.4 The Adaptive Tool:

The adaptive tablet-learning tool was developed as an Android mobile application using PHP and the MySQL database management system. The control group learners were asked to use the traditional school e-learning Moodle where they get access to all of the available materials of the selected course, and they manually select the materials based on their preferences. The experimental group learners are asked to use the adaptive tablet-learning tool and complete the following steps.

Step#1: Create an Account: When using the system for the first time, the experimental group learners needed to create an account and provide basic data (login, password, preferred material format: PDF/ Power Point/ Audio/ Video, preferred material language: Arabic/ English, and self-reported topic knowledge level: low/intermediate / high).

Step#2: Login: Learners login to the system using their login and password and learners have the option to change their basic data at any time.

Step#3: User-Context Adaptive Material: Learners receive a list of course materials that is filtered by their preferred language and level.

Step#4: Device-Context Adaptive Material: Based on the device battery and connectivity conditions, a score for each material format is calculated. The format with the highest score is used to present the course material.

3.5 Experimental Design:

A user experiment was conducted to investigate the feasibility and efficacy of improving the learning outcomes of a tablet-based adaptive learning program using personalized content via implicit indicators, a satisfaction survey, and a performance assessment. The experiment consisted of four main stages.

Orientation Session: The experiment starts with an orientation session with participants that informed them that the objective of the session was to explore a better design of the school's e-learning tool. Participants were informed that all activities that they perform on the tablets in the lab will be recorded using software and that they have the right to quit the 30-40 minute experiment at any time.

Implicit Indicator Measurement: Participants were asked to use the tablets and access the course material by using the traditional e-learning tool or the tablet-adaptive tool, which corresponded with the control group and the experimental group, respectively. During the sessions, the *Morae Recorder* software is used to remotely observe participants' interactions with the tools. The dwell time to read each material was automatically calculated by subtracting the difference in the start time (T1) when a participant selects a material and T2 when the same participant starts to read/watch course material (for example, Material-1), and the difference between T2 and T3 when the participant leaves Material-1. The dwell times are the difference from T1 to T2 and the difference from T2 to T3. For identical materials that were viewed at different times (for instance, if the participant returns back to Material-1), the T2s were accumulated to calculate the total dwell time for each material. Since the Internet connectivity inside the school lab is constant, in this part of the experiment, it is expected that the adaptive tool will not consider the connectivity factor.

Learning Process: All participants were given the tablets to learn the course at home for one week using the traditional e-learning tool or the tablet-adaptive tool, which corresponded to the control group and the experimental group, respectively. Learners were encouraged to use the tools in different locations while they were mobile. In this part of the experiment, the adaptive tool will consider the connectivity factor. It is expected that learners will face different connectivity conditions at their homes and while mobile in different locations.

Post-Test and Feedback Questionnaire:

After learning the course for a week at home using the two different tools, the participants in the two groups returned to the school lab and completed a post-test to compare the learning performances of the experimental and control groups. The test items were anonymously designed and corrected by a teacher of the course at grade 12 of the school. The teacher was not aware of the main objective of the research. Following the post-test, all participants completed a feedback questionnaire assessing perceived usefulness and willingness to use. Perceived usefulness was assessed by 3 items: (1- Using the system would increase the efficiency of my study, 2-The system would make it easier to keep track of learning materials, 3-The system would be useful for me as a student), adopted from (Gaoa et al., 2011) with Cronbach's Alpha 0.835. Intention to use was assessed by 2 items (1- Assuming I have access to the system, I intend to use it, 2- Given that I have access to the system, I predict that I would use it), adopted from (Gaoa et al., 2011) with Cronbach's Alpha 0.906. The questionnaire also included items that collect participants' demographic data and specify the course formats that were selected by the learners (for the non-adaptive tool users) and those that were suggested by the tool (for the adaptive tool users). An open ended question that collects participants' overall feedback about the experiment was also included. Feedback in general confirmed that participants could perform the experiment with minor difficulties.

The experimental sessions were conducted within the month of September 2018 in the students' school computer lab, which was equipped with tablets with 3G Internet connectivity. All tablets were alike and operated on the Android 4.0 operating system with a 1.6 GHz processor, 1GB of RAM, a 32 GB hard disk, and a 9.7 inch screen. This is the same configuration as the tablets that are planned to be distributed to secondary stage students within the new Egyptian education system.

3.6 Data Analysis and Results

The overall data that were collected in this study are displayed in **Table 1**.

Course Format:

In the feedback questionnaire, participants reported on the format that they used for learning the course outside the school. In the case of the non-adaptive tool, the format was selected by the participants themselves, while the adaptive tool, the system suggested the format based on the score, as discussed in the sections above. It was noted that the majority of participants from the non-adaptive group selected the video format, while for the same content, the adaptive tool selected PDF as the most suitable format. This adaptive suggestion was most likely based on the device connectivity and battery conditions.

Table 1: Overall Collected Data

	Non- Adaptive m-learning Tool	Adaptive m-learning Tool
Demographics	**Number- %**	**Number- %**
Number of participants	15	16
Female participants	9	10
Self-Reported knowledge level of e-learning skills	49% intermediate 51% high	50% intermediate 40% high
Selected/ Suggested Format	**Selected**	**Suggested**
# of times PDF was selected by participants/ suggested by the tool	3	6
# of times PPT was selected by participants/ suggested by the tool	5	5
# of times Audio was selected by participants/ suggested by the tool	1	3
# of times Video was selected by participants/ suggested by the tool	6	2
Willingness to Use	**%**	**%**
I will use the tool frequently in this academic period	45	94
I will use the tool heavily during my studies in the future	45	94

Perceived Usefulness	**% Strongly Agree/ Agree**	**% Strongly Agree/ Agree**
I would recommend this e-course to friends/colleagues	61	95
I have learned a lot in this course	57	62
I have enjoyed taking this course	73	**96**
Dwell Time	**Time (min)**	**Time (min)**
Mean Dwell Time of reading/ watching materials	33.10	50.19
Calculated t-value	**2.75**	

Willingness to Use (*Use*):

The willingness to use *(USE)* construct reflects the strength of one's intentions to use the system in the future. The *Use* construct was measured by two items that were adopted from a study assessing the use of Moodle e-learning (Islam et al., 2013). The two items, which were measured using a five-point Likert scale with choices ranging from "Strongly disagree (1)" to "Strongly agree (5)", were reported to be reliable and were stated as follows "I will use the tool frequently in this academic semester" & "I will use the tool heavily during my study in the future". A significant majority (94%) of the adaptive m-learning tool users cited that they strongly agree or agree with the statement that they are willing to use the adaptive system in their current and future studies, while only 45% of the non-adaptive tool users expressed that they strongly agree or agree that they are willing to use the system in the future. Such a significant difference in the responses of the two different groups confirms the hypothesis that context-based adaptive tools could increase the learners' willingness to use m-learning contents.

Perceived Usefulness (*P Usefulness):*

The Perceived Usefulness construct reflects the users' satisfaction with the learning environment. The Perceived usefulness was measured in this study using an explicit indicator (the user explicitly rates the system by answering rating questions: *P Usefulness*) and an implicit indicator (Dwell time, the amount of time spent on the system, which was unobtrusively collected using a recording software during the use of the system: *Dwell*)

The explicit measure of perceived usefulness (*P Usefulness*) was measured using three items that were adopted from a study assessing an online MBA system using a survey of online MBA students (Peltier et al., 2003). The three items, which were designed using a five-point Likert scale with choices ranging from "Strongly disagree (1)" to "Strongly agree (5)", were reported to be reliable, and stated as follows: "I would recommend this e-course to friends/colleagues", "I have learned a lot in this course", & "I have enjoyed taking this course".

A significant majority (96%) of the adaptive m-learning tool users cited that they strongly agree or agree with the statement that they enjoyed taking the course, while 95% reported that they would recommend the tool to friends/ colleagues. However, only 73% of the non-adaptive tool users cited that they strongly agree or agree with the statement that they enjoyed taking the course and only 61% reported that they would recommend it. When answering the question "I have learned a lot in this course", a small difference was observed between the responses of the two groups. 62% of the adaptive m-learning tool users expressed that they strongly agree or agree with the statement that they learned a lot, while 57% of the control group stated they learned a lot from the course. This result can be justified similarly to the low learning performance of the two groups, as discussed above, due to the short period that was given for the participants to study the course. While the variation between the two groups' responses concerning the learning benefits of the two tools is not significant, still, overall, the learners' perception of the usefulness of the adaptive tool is significantly higher compared with the learners using the non-adaptive tool. Such a significant difference in responses between the experiment and the control groups confirms the hypothesis that the context-based adaptive tools could increase the learners' perception of m-learning contents' usefulness.

Dwell Time (*Dwell*):

Significant differences in the dwell times for the same content were observed when comparing the time that was spent by the participants from the two different groups reading and watching materials. The participants using the adaptive m-learning tool spent significantly more time (mean: 50.19 minutes) learning from adapted materials compared to the participants from the traditional e-learning group (mean: 33.10 minutes) learning from the same, but not adaptive, materials in the same course. This significant difference (t=2.75) suggests learners' engagement and the materials' usefulness (Kelly, 2004).

Correlation between Dwell Time and Perceived Usefulness*:*

The relationship between the implicit indicators of perceived usefulness (*Dwell*) and the explicit ratings of perceived usefulness (*P Usefulness*) was examined using the Pearson correlation. Significance testing was employed to ensure that the results from the Pearson correlation were not random, and a confidence interval of 95% and a statistically significant coefficient of $p < 0.05$ are accepted (Akuma et al., 2016). Based on the Pearson correlation between the implicit indicators & explicit ratings for the two groups, a positive correlation was observed between the explicit usefulness rating and the implicit indicators that were measured using Dwell time, thereby providing more confidence to the results that were obtained by each indicator alone.

Learning Outcomes (*Learn*):

The post-test was designed by a single teacher who teaches the selected course at the participants' school. The same teacher corrected all tests using the same criteria. The test scores were used as a means of comparison of the learning performance of the control versus the experimental groups. The test scores were compared using the Mann-Whitney test, and the scores of the two groups did not follow a normal distribution, which was most likely due to the small sample sizes in the two groups (15 and 16 participants). In general, all learners from the two groups scored low in the post-test, and no significant differences were found between the test scores of the two groups. A very small difference was observed in the scores, suggesting that the experimental group outperformed the control group, but this difference was statistically insignificant (p=.253). This result is not enough to support the hypothesis that context-based adaptive m-learning tools could increase learning performance. The participants of the two groups were given only one week to learn the course at home, which represents one of the current study limitations. Such a short period of time could justify the low learning outcomes for both groups.

Open-ended Question Analysis

In total, eight (25.8%) participants provided open text comments about their general experience with the two versions of the m-learning tool. The responses of those who used the adaptive tool included a number of positive comments that mainly concerned the suitability of the suggested content level and the format based on their predefined level of knowledge and the devices' Internet connectivity in various conditions. For example, one participant stated the following:

> *"I enjoyed learning the course in different locations and timing….. The format and content were just right"*

However, two of the non-adaptive tool group expressed their frustration from trying to watch video materials that they selected while they were moving.

> ***"****The best timing for me to watch the materials was on the run, in the school bus….it was so frustrating, videos freeze, break, won't load, or won't even appear… "*
>
> ***"****I did not complete all the materials of the course, I selected the video option, and It was so painful to watch videos with a slow net mobile in some places …I wanted to carry these materials everywhere, every time…"*

4. CONCLUSION & IMPLICATIONS

While mobile learning tools have the potential to improve how people learn, they suffer from low engagement and a lack of personalization (Sahid et al., 2018). Over the past few years, several studies have suggested context-based adaptive mobile learning models based on various learning contexts. Little research has assessed the learning benefits of these models. This pilot study suggested and empirically assessed a context-aware adaptive m-learning tool using an experiential real case environment using an implicit indicator. The study included convenient sample of 31 students and examined the learners' perceived usefulness of the adapted materials, their learning performance, and the learners' willingness to use these systems by comparing the experiences of school students using two versions (adaptive and non-adaptive) of a tablet-based e-learning tool. The assessment was done using an implicit measure (dwell time), an explicit measure (satisfaction questionnaire), and a learning assessment (post-test).

The effect of the context-aware m-learning tool on learners' perceived usefulness of the adapted materials was assessed in this study using an implicit indicator (dwell time in an experimental setting) and an explicit indicator (survey after a week of using the tool). Both indicators suggested that the learners' perceived usefulness of the adapted content was significantly higher compared with the learners of the non-adaptive tool. A positive correlation was observed between the explicit and implicit feedbacks, thereby providing more confidence to the results. However, the results of the survey suggested that a context-based adaptive tool increases the learners' willingness to use m-learning contents. The qualitative data that were collected from learners after a week of using the tools also confirmed this result since learners expressed that they enjoyed learning with the adaptive tool. However, the use of video caused frustration and dissatisfaction with the non-adaptive tool, leading to students stopping using the contents since they were not adapted to the mobile context of the use with weak battery and connectivity conditions.

It worth mentioning that the results suggest that all students from both groups prefer the video format and accessing course materials while mobile in school buses or cars. Hence, an adaptive tool that automatically selects the best suited material format based on the battery charge and Internet connectivity conditions is preferable and can motivate one to continue learning the course. These results, reflecting positive attitudes towards the adaptive tool in terms of the perceived usefulness and willingness to use, support previous work reporting general *good* attitudes towards adaptive learning systems (Gomez et al., 2016).

Concerning the effect of the adaptive m-learning tool on improving learning performance, the results suggested that, in general, all learners from the two groups scored low in the post-test, and no significant differences were found between the test scores of the two groups. Additionally, modest percentages (62%) of the experimental group and the control group (57%) expressed that they learned a lot from the course. This result contradicts a previous finding (Garcia –Cabot et al., 2015), suggesting that students using the adaptive tool outperformed students using the non-adaptive tool in practical assignments and in overall scores in an academic semester. These unexpected results might be due to the short learning period (a week) that was given to students to learn the course, which represents a limitation of the current study.

These findings have theoretical and practical implications as follows.

This research provides a number of theoretical contributions to the existing adaptive m-learning models. The importance of assessing adaptive models in terms of learning benefits and learners' perception of the usefulness of the adapted materials are highlighted. Additionally, the use of implicit indicators as reliable measures of documents' usefulness in the adaptive m-learning context is supported. The results suggest a positive correlation between learners' explicit rankings and implicit indicators for the adapted materials' usefulness. The current study also validated a score-based model, by calculating scores for each content format based on user and device context.

There are practical implications from this research for the designers of m-learning tools targeting undergraduate students. Designers need to understand the learning context within which these learners actually use the tools. The results of the current research suggest the preference for mobile use, depending on the mobility of the m-learning. Students also prefer learning materials in video formats, which requires reliable battery and Internet connectivity conditions. Hence, the value of a context-aware tool that adapts the format of the learning material is significant. The current study validated a score-based model by calculating the scores for each content format based on the user and device contexts. Based on this result, education ICT-based reform movement, such as the Egyptian new education system (EDU 2.0) should ensure the establishment of reliable digital infrastructure at least at the school level. As students without access to reliable mobile devices and high-speed internet are at a distinct disadvantage when it comes to learning on adaptive m-learning systems, policy makers of such new reform would consider the ICT infrastructure as a priority to guarantee digital equity within learners nation-wide.

5. LIMITATIONS & FUTURE WORK

As with any experiment, there are some limitations to the current study. Sampling is one of these limitations since our sample was limited to the same geographical and cultural context, which affects the generalization of the results. In this study, participants were selected according to a convenience sample that required having intermediate to advanced e-learning skills and attendance at the same private school in Cairo. This may not reflect the behavior of average Egyptian school students. Learning outcomes, perceived usefulness, and willingness to use the adaptive tool might vary for students with demographic characteristics that are different than the participants of this study. Additionally, using dwell time as the sole implicit indicator might be restricted to the experimental environment that was adopted. Furthermore, assessing learning performance with a post test with no pre-test and after only a week of learning might affect the measure of learning benefits, which might justify that no improvement in learning performance was found. Future work might consider more longitudinal research to assess long term benefit during a school year or semester, integrate more implicit indicators and use a larger sample. It would be as well interesting to assess students' performance in the following grade after having been exposed for year to the content through the m-learning system. Future investigational research might also try to correlate the increased engagement of the student in learning with the adaptive m-learning system and long term knowledge gains or retention.

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