*International Journal of*
*Emerging Research in Management &Technology*
*ISSN: 2278-9359 (Volume-6, Issue-6)*

**Research Article** | **June 2017**

# Factors Influencing the Acceptance of M-Learning by Students of Higher Education in Morocco

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***Abstract:***

***The M-learning plays an increasingly important role in the development of teaching methods in higher education. However, the success of M-learning in higher education will depend on the acceptance of users of this technology. The purpose of this article is to study the factors that impact the intentions of college and university students to accept M-learning. Based on the Unified Theory of Acceptance and Use of technology (UTAUT) [18], this research proposes a model to identifying the factors that influence the acceptance of M- learning in the Higher education of Morocco. A structural equation model was used to analyze the data collected from 193 students. The findings of this study indicate that factors such as the "ease of use" and the "quality of service" influence the intent to use M-learning while others like the "expected performance", the " personal Innovativeness" and the "influence of professors" have no impact on the intent of using M-learning.***

***Keywords: M-learning; Acceptance of technology; Intention to use, UTAUT model, students' behavior.***

## I. INTRODUCTION

Nowadays, the Internet has changed how people communicate. The new digitalized world facilitates communication and connects millions of people who build online relationships. These latter are developing at an astonishing rate. Therefore, it seems normal that pedagogical practices are influenced by this change.

Furthermore, the rapid spread of mobile devices and wireless networks in colleges and universities makes higher education an appropriate place to integrate student-centered e-learning.

In this context, M-learning is a new step into the development of e-learning and distance learning. It is defined as any learning done through mobile wireless devices such as smart phones, tablets and personal computers (PC.) These devices allow users to learn anytime and anywhere [14].

In the era of skilled users of ATAWADAC (Any Time, Any Device, Any Content), learning becomes mobile and uses ubiquitous methods.

Thus, this approach seems to be the future of higher education since these devices (tablet, PC, Smartphone) are more popular among students.

These mobile devices have become more affordable, efficient and easy to use, and can extend the benefits of e-learning by offering college and university students the opportunity to access course materials and ICTs and learn in a more collaborative approach environment [15].

However, adopting M-learning sometimes raises some pedagogical problems related to the use of mobile devices in the classroom, which may disrupt the learning process.

In addition, some college and university professors are reluctant to adopt this technology or have difficulty trying to use it effectively, as this new technology may require considerable efforts to implement [2].

In Morocco 80% of youngsters between 12 and 24 have a smartphone, 76% spend more than 3 hours on internet however only 29% of them use the web for educational purposes. Faced with this fact, we may think that users may not be willing to accept M-learning which lead us to ask the following question: what motivates youngsters to engage in "digital" learning in general and Mobile learning in particular?

More precisely, we would like to understand the attitude of students towards M-learning their motivations and constraints in order to identify the key factors to accelerate adoption of this technology. The objective of this article is, then, to study the factors that influence the acceptance by college and university students of M-learning.

## II. CONCEPTUAL FRAMEWORK

To examine the attitude of users, a number of models have been developed to examine the acceptance and intention of individuals to adopt new technologies in the world of information systems. In this context, Davis [5] attempted to determine what makes people accept or reject information technology. The most widely used model in the adoption of technology is the Technology Acceptance Model (T.A.M) [5]. The idea behind TAM is to provide a theoretical framework explaining the impact of external variables (e.g. objective characteristics of the system, training, self-efficacy) on internal beliefs, attitude towards use, behavioral intentions and actual use of the system [9].

 

Another popular and recent model in the acceptance of information technology is the unified theory of acceptance and use of technology (UTAUT). This theory has been proposed by Venkatesh et al. [18] and attempts to integrate and to empirically compare components from different models of the technology acceptance.

The UTAUT comprises four determinants of computer user behavior and four moderators who are judged to moderate the effect of the four determinants on the behavioral intent and behavior of the user. UTAUT believes that the perceived ease of use, perceived usefulness, social influences and facilitating conditions are direct determinants of the user's intent or behavior. This gives a significant improvement in the explanatory power of the model. Similarly, moderator variables (gender, age, experience and context of use) are very important for understanding the characteristics of different users' groups.

Venkatesh et al. [18] indicate that UTAUT has the capacity to explain approximately 70% of the variance of user's intent. It has been shown that UTAUT surpasses other previously mentioned models [18] as it can provide a useful tool for end users to assess the success of new technology [9].

## III. THE MODEL

In this section, we will discuss the constructs of the proposed model.

**Expected performance (EP)**

Venkatesh et al. [18] defined performance as the extent to which a person believes that the use of an information system may benefit him or her in terms of task performance. They also organized five constructs based on previous models that refer to the expected performance: perceived usefulness, extrinsic motivation, work compatibility, relative advantage and expectation. In addition, they also indicated that the expected performance is a stronger predictor than the behavioral intent to use technology.

Furthermore, Davis [5] demonstrated that the perceived utility is the most frequently used factor in deciding on more or less higher adoption rate. Applying the expected performance to an M-learning framework assumes that students find M-learning useful because they learn at their convenience and in a quick pace. It will also improve their learning productivity [19]. This leds us to testing the following hypothesis:

**H1: The expected performance will have a positive effect on the intent to use M-learning.**

**Ease of use (EU)**

Venkatesh et al. [18] defined the expectation of effort as the degree of ease to which individuals think they have when using an information system. The constructs of previous models related to the concept of stress expectation are the ease of use and complexity which means that the ease of use of a designed information system is one of the key factors in the acceptance of information technologies. Previous researches indicate that the expectations of individuals in regards to the use of a system may differ due to gender, age and experience. As a matter of fact, researchers support that the notion of stress expectancy will be a stronger determinant of individual intention for females , especially those with a weak experience with the system [18]. Based on UTAUT, we expect that students' acceptance of an M-learning system depends on the ease of use.

**H2: The ease of use will have a positive effect on the intent to use M-learning.**

**Influence of professors (IP)**

The influence of professors is derived from social influences, which are defined as the extent to which an individual perceives it is important for others to believe that he or she should use the new information system [18]. Previous studies indicate that social influences are a direct determinant of an individual's behavioral intent to use new technologies. In this study, social influence refers to the influence of professors, which is defined as the extent to which professors directly encourage their students to use e-learning services [3]

The influence of professors is an important element in encouraging students to adopt new technologies to their learning environment. This led us to testing the following hypothesis:

**H3: The influence of professors has a positive effect on the intent to use M-learning.**

**Quality of service (QS)**

A number of researches on human-machine interaction and usability [6] define quality of service in terms of reliability of response, quality of content and security. Most definitions of service quality have focused on customer perception and satisfaction of the offered services. Parasuraman, Zeithaml and Berry [16] defined consumers' expectations of quality of service as what they think a service provider should offer rather than what they would offer.

The excellence of services provided to users can affect the level of acceptance of new technologies. Lee [11] reported that students' perception of the quality of online service could be seen as a key factor affecting their behavioral intent towards accepting e-learning [3]. Thus, this led us to test the following hypothesis:

**H4: The quality of service has a positive effect on the intent to use M-learning.**

**Personal Innovativeness (PI)**

Agarwal and Prasad [1] define "innovativeness" as the willingness of the individual to try out any new information technology. They suggest that individuals with a high level of innovativeness are more willing to adopt positive ideas and changes in new information technologies and have more ability to cope with uncertainty than others [12].

 

Thus, students with a high capacity for personal innovativeness are expected to be more risk-takers and have a more positive intent to use M-learning in their study [3]. Therefore, the following hypothesis was tested:

**H5: Personal innovativeness has a positive effect on the intent to use M-learning.**

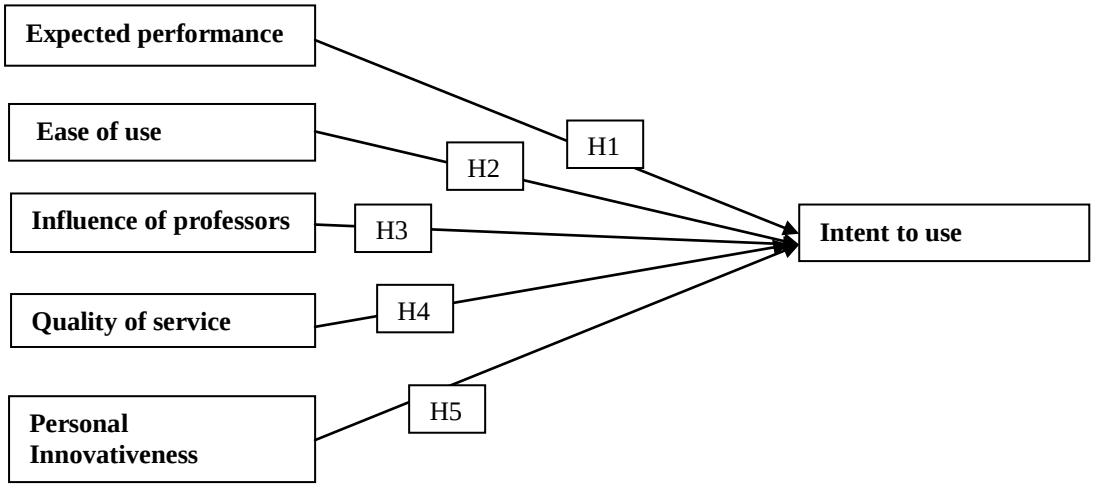


Fig. 1 The model

## IV. RESEARCH METHODOLOGY

Our questionnaire consisted of 26 items measuring six constructs that were drawn from different research frameworks and were adapted to the context of M-learning. This study used the convenience sampling technique to collect data. The questionnaire was distributed to students from different Moroccan school, colleges and universities. A brief description of the research objectives and a definition of M-learning were given beforehand to the students who completed the questionnaire. A total of 200 responses were obtained. Seven incomplete questionnaires were rejected. We report the data and characteristics of the 193 participants in Table I

Table I: Characteristics of the Sample

| Internet connection tool | | | | | |
|---|---|---|---|---|---|
| | | Number of employees | Percentage | Valid percentage | Accumulated percentage |
| valid | smartphone | 123 | 63,7 | 63,7 | 63,7 |
| | laptop | 48 | 24,9 | 24,9 | 88,6 |
| | Tablet | 22 | 11,4 | 11,4 | 100,0 |
| | Total | 193 | 100,0 | 100,0 | |
| Connection time | | | | | |
| | | Number of employees | Percentage | Valid percentage | Accumulated percentage |
| valid | More than 4h | 130 | 67,4 | 67,4 | 67,4 |
| | Between 2 to 3h | 40 | 20,7 | 20,7 | 88,1 |
| | Between 1 to 2h | 17 | 8,8 | 8,8 | 96,9 |
| | Less than 1h | 6 | 3,1 | 3,1 | 100,0 |
| | Total | 193 | 100,0 | 100,0 | |
| **Gender** | | | | | |
| | | Number of employees | Percentage | Valid percentage | Accumulated percentage |
| valid | Male | 70 | 36,3 | 36,3 | 36,3 |
| | female | 123 | 63,7 | 63,7 | 100,0 |

 

| | | | | | |
|---|---|---|---|---|---|
| | Total | 193 | 100,0 | 100,0 | |
| Level of study | | | | | |
| | | Number of employees | Percentage | Valid percentage | Accumulated percentage |
| Valid | bac+1 | 14 | 7,3 | 7,3 | 7,3 |
| | bac+2 | 56 | 29,0 | 29,0 | 36,3 |
| | bac+3 | 35 | 18,1 | 18,1 | 54,4 |
| | bac+4 | 42 | 21,8 | 21,8 | 76,2 |
| | bac+5 | 46 | 23,8 | 23,8 | 100,0 |
| | Total | 193 | 100,0 | 100,0 | |

## V. MAIN FINDINGS

Our approach to data analysis is of two steps. The first step of evaluating the measurement model is to check if the model presents a good fit to the data collected and the second step (structural model) is to underway hypothesis tests.

### *A) Measurement model*

Exploratory factor analysis was performed at the beginning using a Varimax rotation principal component analysis to extract the six factors using SPSS 20. Confirmatory factor analysis was then performed using AMOS 18 to evaluate the measurement model in terms of measurement reliability, convergent validity and discriminant validity.

Convergent validity can be evaluated using three criterion as recommended by Fornell and Larcker [8]: (1) loading greater than 0.50; (2) CR composite reliability greater than 0.7 and; (3) the Converging Validity Index (CVI) should exceed 0.5.

As shown in Table II, the results indicate that all constructs correspond to their respective items. All saturation coefficients are above the threshold of 0.50. Five items PIN3, QS1, QS2, QS3 and QS5 were eliminated due to saturation levels are less than 0.50. The Cronbach alpha values range from 0.702 to 0.911 and are above the threshold value of 0.7. Composite reliability values (CR) are greater than 0.7 and the converging validity indices are all above the recommended level of 0.5, indicating good internal consistency [8].

Table II: Convergent Validity.

| Construct | Extracted factor | Aplha of Cronbach | Standardized factor | $R^2$ | CVI | CR |
|---|---|---|---|---|---|---|
| Ease of use | | 0,702 | | | 0,581 | 0,846 |
| EU1 | ,694 | | 0,803 | 0,363 | | |
| EU2 | ,707 | | 0,716 | 0,267 | | |
| EU3 | ,796 | | 0,69 | 0,476 | | |
| EU4 | ,725 | | 0,83 | 0,377 | | |
| Expected Performance | | 0,828 | | | 0,551 | 0,86 |
| EP1 | ,771 | | 0,73 | 0,533 | | |
| EP2 | ,794 | | 0,739 | 0,546 | | |
| EP3 | ,824 | | 0,747 | 0,559 | | |
| EP4 | ,705 | | 0,812 | 0,374 | | |
| EP5 | ,760 | | 0,678 | 0,46 | | |
| Influence of professors | | 0,818 | | | 0,57 | 0,798 |
| IP1 | ,920 | | 0,877 | 0,769 | | |
| IP2 | ,920 | | 0,774 | 0,599 | | |

 

| | | | | | | |
|---|---|---|---|---|---|---|
| Personal Innovativeness | | 0,736 | | | 0,641 | 0,744 |
| PIN1 | ,891 | | 0,947 | 0,897 | | |
| PIN2 | ,891 | | 0,621 | 0,386 | | |
| Quality of service | | 0,769 | | | 0,641 | 0,784 |
| QS4 | ,903 | | 0,709 | 0,502 | | |
| QS6 | ,903 | | 0,888 | 0,788 | | |
| Intent to use | | 0,911 | | | 0,656 | 0,905 |
| IU1 | ,863 | | 0,807 | 0,652 | | |
| IU2 | ,883 | | 0,83 | 0,689 | | |
| IU3 | ,809 | | 0,762 | 0,58 | | |
| IU4 | ,890 | | 0,856 | 0,732 | | |
| IU5 | ,853 | | 0,794 | 0,63 | | |

To examine discriminant validity, this study compared the square root of the CVI for each construct and the correlation between this construct and any other construct). If the square root of the CVI of a construct (diagonal value) is larger than the elements in the corresponding rows and columns, this indicates that each construct is more closely related to its own measurements than to those of other constructs [8]. As it can be seen in Table III, the square root of the CVI of all constructs is greater than the correlation estimate with the other constructs. To sum up, the measurement model has sufficient reliability, convergent validity and discriminant validity.

Table III: Discriminants Validity

| VARIABLE | EU | EP | IP | PIN | IU | QS |
|---|---|---|---|---|---|---|
| EU | **0,76223356** | | | | | |
| EP | 0,685 | **0,74229374** | | | | |
| IP | 0,512 | 0,579 | **0,75498344** | | | |
| PIN | 0,724 | 0,479 | 0,464 | **0,80062476** | | |
| IU | 0,698 | 0,64 | 0,426 | 0,526 | **0,80993827** | |
| QS | 0,666 | 0,465 | 0,518 | 0,738 | 0,349 | **0,80062476** |

The figures in bold on the diagonal represent the square root of the CVI; The off-diagonal elements are the correlation estimates.

***B) Structural model and hypothesis testing***

The results of the exploratory phase used exploratory factor analysis. The quality of the adjustment of model to the data was verified using the most common indices: the khi-2 / ddl ratio, the GFI, the AGFI, the NFI, the CFI, the TLI and the RMSEA. The results obtained are satisfactory (see Table IV).

Table IV: Results of Adjustment Model

| Adjustment index | Recommended value | Findings |
|---|---|---|
| khi-2/ddl | <=3 | 1.437 |
| GFI | >= 0.9 | 0.9 |
| AGFI | >= 0.8 | 0.861 |
| NFI | >= 0.9 | 0.897 |
| CFI | >= 0.9 | 0.966 |

 

| | | |
|---|---|---|
| TLI | >= 0.9 | 0.957 |
| RMSEA | <= 0.08 | 0.048 |

***C) Testing of research hypotheses***

In the last step, a structural equation analysis was conducted to estimate the causal relationships between the dimensions of the research model. The study of the significance of standardized regression coefficients (see Table V) led us to confirm certain hypotheses and to reject others. The hypothesis H2 "the expected performance has a positive effect on the intent of use" is rejected as well as the hypothesis H3 " the influence of professors has a positive effect on the intent to use M-learning." and the hypothesis H5 " Personal innovativeness has a positive effect on the intent to use M-learning ". On the other hand, the hypothesis H1 «The expected performance will have a positive effect on the intent to use M-learning " is validated. Finally, a positive link can be established between the quality of service and the intent to use, thus the hypothesis H4 is validated.

Table V: Validity of Research Hypotheses

| tested link | Estimation | S.E. | C.R. | P | Validation of the hypothesis |
|---|---|---|---|---|---|
| IU <--- EU | 0,729 | 0,318 | 2,295 | 0,022 | H1 validated |
| IU <--- EP | 0,289 | 0,185 | 1,565 | 0,118 | H2 non validated |
| IU <--- PIN | 0,223 | 0,148 | 1,505 | 0,132 | H3 non validated |
| IU <--- QS | 0,38 | 0,16 | 2,381 | 0,017 | H4 v validated |
| IU <--- IP | 0,061 | 0,104 | 0,581 | 0,561 | H5 non validated |

## VI. DISCUSSION AND CONCLUSION

The results indicate that the proposed model adequately explains and has the ability to predict the behavioral intent of students to adopt M-learning ($R^2 = 0.58$).

The ease of use was shown to have a significant influence on students' intention to use M-learning [19], [3]. The findings of this research indicate that the ease of use is a good predictor of the behavioral intent to use M-learning ($\beta = 0.729$). This result means that students think that the M-learning system will be easy to use and will not require much instruction on how to use it. So, this might lead M-learning designers to provide easy-to-use, user-friendly M-learning applications to higher education students [19].

Quality of service was also considered to have a significant influence on the behavioral intent to adopt M-learning as students will be ready to adopt an e-learning system when the quality of the service offered is considered good and beneficial to their studies. This confirms the findings of Agarwal et al. [1], Park et al.[17] and Abu-Al-Aish, A & Love, S. [3].

In contrast with the literature review, expected performance, influence of professors and personal innovativeness are not important determinants of behavioral intent [3]. It seems that these factors do not influence students in their M-learning intent to use.

This study showed the applicability of the UTAUT theory in explaining the acceptance of students to M-learning. It is important for practitioners to motivate students about the benefits of M-learning in university studies. In addition, mobile learning designers must design applications that are easy to use and can improve student performance. The ease-of-use and usefulness of a mobile learning system can be of added value to the existing learning system thanks to improved learning and improved students' intent to use of M-learning.

The quality of service offered by e-learning systems should include user-friendliness, fulfilling all student needs and be an up-to-dated as this will attract more students to use M-learning.

In conclusion, the results indicate that higher education institutes need to develop strategic plans and provide guidelines that take into account student acceptance and include all success factors for the sustainable deployment of M-learning. The results of this study can help to understand which factors must be taken into consideration when designing an M-learning system for higher education.

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