# Factors Affecting the Adoption of e-Learning: A Meta-analysis of Existing Knowledge

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***Abstract* — There are different factors that can influence a learner's decision on how and when they will use a particular, innovative e-learning technology. In the existing literature, there are many studies that deal with the identification of factors and their impact on a user's acceptance of e-learning technology. This paper demonstrates the results of a meta-analysis – a statistical synthesis method that provides the opportunity of viewing the research context by combining and analyzing the quantitative results of several independent empirical studies. The meta-analysis was conducted on the basis of empirical data gathered from 28 independent empirical studies in the field of e-learning acceptance. The meta-analysis provided strong evidence that perceived usefulness is the strongest predictor of a learner's adoption of an e-learning technology.**

***Keywords- e-learning, technologies adoption, meta-analysis, TAM, UTAUT, Hedges g***

## I. INTRODUCTION

E-learning is a way of learning that is supported by information communication technologies (ICT) and services, and that makes it possible to deliver education and training to anyone, anytime and anywhere [1]. We can also say that e-learning is a term that stands for all types of technology-enhanced learning services and processes, including web-based learning, virtual classrooms, and digital collaboration [2]. E-learning technologies are not only being used by educational organizations. Recently, and in the business sector especially, companies have been recognizing the benefits of using e-learning technologies that can provide cost-effective on-line courses to their employees.

In order to succeed, e-learning technologies must have a positive impact on the learners. When the learner is presented with a new e-learning technology or service, there are different factors that influence their decision on how and when they will use a particular e-learning technology or service. In the existing literature, we can find many studies that deal with the identification of factors that influence a user's behavioral intentions and the actual use of an e-learning technology. These studies are usually based on acceptance theories and approaches that have been developed and continuously improved over the last two decades.

This paper is organized as follows: in the next section, the main acceptance theories are presented. The third section describes the research methodology of our study. In the subsequent section, the results of the data analysis are given. In the last section, we conclude the paper with a discussion of the results and the implications of the results of the present study.

## II. ACCEPTANCE AND USE OF IT

According to Venkatesh et al. [3], there are different streams of research that deal with answering how and why individuals adopt new information technologies. One stream of research focuses on the individual acceptance of IT, where a user's behavioral intentions or actual use is used as a dependent variable. In the second stream, there are studies that focus on implementation success at the organizational level. In existing literature, we also found a large amount of studies that deal with the conformance level of the technology with the tasks that the end users must complete by using specific information technology. **Figure 1** shows a basic conceptual framework of acceptance models explaining individual intentions for using information technology and the actual use of information technology.

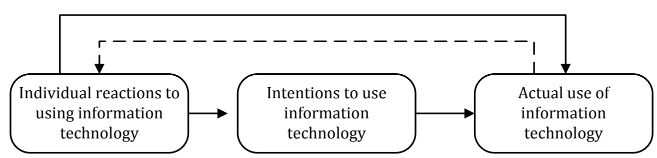


Figure 1 - Basic Concept underlying User Acceptance Models **[3]**

One of the most widely technology acceptance theories being used is the technology acceptance model – TAM [4]. Davis proposed TAM to explain the potential user's behavioral intentions of using a technological innovation. TAM is based on the theory of reasoned action – TRA [5], which is a psychological theory that can be used to explain behavior. The Motivational Model (MM) is another psychological theory that is often being employed in studies dealing with the factors that have an impact on the end user's motivation in the use of an information technology. Venkatesh et al. [3] reviewed existing literature and empirically compared eight theoretical models: TRA, TAM, MM, TPB, the combined TAM and TPB, Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT). In the same study, the authors introduced and validated a new theoretical model, called the Unified Theory of Acceptance and Use of Technology (UTAUT). Table I provides a list of independent

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and dependent variables, specified by individual acceptance theoretical models.

TABLE I. INDEPENDENT VARIABLES AND DEPENDENT VARIABLES IN ACCEPTANCE MODELS

| Theory | Independent variables | Dependent Variables |
|---|---|---|
| TRA | attitude toward behavior (ATB), subjective norm (SN) | behavioral intentions (BI), actual use (U) |
| TAM | perceived usefulness (PU), perceived ease of use (PEOU) | attitude toward use (ATU), behavioral intentions (BI), use (U) |
| MM | intrinsic motivation (IM), extrinsic motivation (EM) | behavioral intentions (BI) |
| TPB | attitude toward behavior (ATB), subjective norm (SN), perceived behavioral control (PBC) | behavioral intentions (BI), actual use (U) |
| MPCU | facilitating conditions (FC), social factors (SC), perceived consequences (PCON), long-term consequences (LTC) | behavioral intentions (BI), actual use (U) |
| IDT | relative advantage (RA), ease of use (EOU), image (IM), visibility (VIS), compatibility (COM), results demonstrability (RD), voluntariness of use (VOL) | behavioral intentions (BI) |
| SCT | computer self-efficacy (CSE), perceived outcomes (POUT), affect (AFF), anxiety (ANX) | use (U) |
| UTAUT | performance expectancy (PE), social influence (SI), effort expectancy (EE), facilitating conditions (FC) | behavioral intentions (BI), actual use (U) |

Most researchers are interested in the structural relationships among constructs in the research model that help explain an individual's acceptance of a technology. The empirical data is usually statistically analyzed using structural equation modeling (SEM). The results of structural equation modeling are usually presented in a set of causal relationships, where each causal relationship is described using the following attributes: independent variable, dependent variable, path coefficient (β), and significance value (p). In the next section, the research methodology is presented together with the research question and data collection process.

## III. RESEARCH METHODOLOGY

In existing literature, we can find different studies reporting different results about the size estimates of path coefficients in common factor relationships. We can find variations in the predicted effects and significance levels in studies with different types of users and e-learning technologies. This fact raises the following research question:

RQ1: *What is the mean effect size of a particular factor (PU, PEOU, etc.) on a user's acceptance (BI, ATU or U)?*

To answer the above-stated research question, we performed a meta-analysis. Meta-analysis allows various results to be combined, taking into account the relative sample and effect sizes [6]. In the meta-analysis, only significant causal relationships were included.

In the systematic literature review, we used the scientific database ScienceDirect for searching relevant studies. The papers included in this study were searched using a combination of:

- *Keywords, related to an acceptance theory* - Technology Acceptance Theory (TAM), Theory of planned Behavior (TPB), etc.
- *Keywords, related to e-learning technologies* - e-learning, elearning, on-line learning, web learning, etc.

We identified 28 journal papers (all the paper references are listed at the references). We developed coding rules to ensure that all studies were treated consistently. The coding dealt with the identification and coding of:

- *Context* – the context, in which the study was performed. Usually with a short description of the e-learning technology.
- *Sample size* – the number of respondents included in the sample frame.
- *Ground theory* – the theory upon which the research model was developed and tested.
- *Independent variable* – the name of the independent variable.
- *Dependent variable* – the name of the dependent variable.
- *Path coefficient* – the size of the path coefficient (β).
- *Significance level* – the p value.

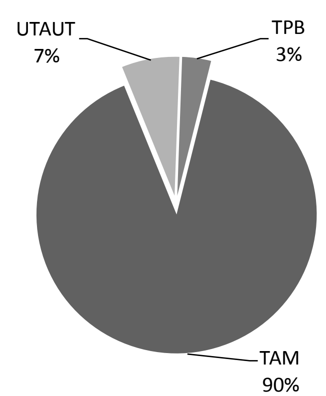


Figure 2 – Summary of theories, on which the reviewed studies were grounded

 

The chart on the Figure 2 reveals, that most of the studies that were reviewed and included in the meta-analysis, used TAM as a ground theory.

TABLE II. SAMPLE SIZE STATISTICS

| | Estimate |
|---|---|
| Total sample size | 8133 |
| Average sample size | 254 |
| Min sample size | 31 |
| Max sample size | 858 |
| Number of students users | 5167 |
| Number of non-students users | 2966 |

Table II summarizes the sample sizes across all studies that were included in the meta-analysis. The lowest sample frame size comprised 31 respondents and the highest sample frame included 858 students.

## IV. DATA ANALYSIS AND RESULTS

### A. Analysis method

Meta-analysis is a statistical technique that can be used to assimilate information from different independent studies. Effect size is the main statistical concept in meta-analysis, which refers to the magnitude of the effect observed in the study, which can be:

- *The size of the relationship between variables*. There are many different statistics that can be used to estimate the effect size, for example: the Pearson product-moment correlation coefficient, r; the effect-size index, d; odds ratios, etc.
- *The degree of difference between group means*. There are different metrics that can be used to describe the differences in the arithmetic means of different studies. These metrics are, for example: Cohen's *d*, Glass's Δ and Hedges's *g*, which was also used in this study.

The basic principle in meta-analysis is to calculate the effect sizes for individual studies, convert effect sizes to a common metric and then combine metrics to obtain an average effect size. This study included several independent studies, therefore the meta-analysis was conducted on a "random effects" basis. The assumption underlying this was that each study included in this study is taken from a population that is likely to have a different effect size to any other study included in the meta-analysis.

In the meta-analysis in this study, we focused on a set of causal relationships, listed in Table 3. Table 3 shows descriptive statistics about causal relationships (independent variable → dependent variable) with the following metrics:

- the number of causal links, evaluated in all studies (N links)
- the number of significant positive causal links found (SIG+)
- the number of non-significant positive causal links found (not SIG+)
- the number of significant negative causal links found (SIG-)
- the number of non-significant negative causal links found (not SIG-)
- the maximum significant positive path coefficient size (SIG+ MAX)
- the minimum significant positive path coefficient size (SIG+ MIN)
- the average significant positive path coefficient size (SIG+ AVE)
- the maximum significant negative path coefficient size (SIG- MAX)
- the minimum significant negative path coefficient size (SIG- MIN)

TABLE III. SUMMARY OF MAIN CAUSAL EFFECTS

| Independent variable | Dependent variable | N links | SIG+ | not SIG+ | SIG- | not SIG- | SIG+ MAX | SIG+ MIN | SIG+ AVE | SIG- MAX | SIG- MIN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PEOU | PU | 26 | 25 | 1 | 0 | 0 | 0.690 | 0.160 | 0.406 | | |
| PU | BI | 17 | 17 | 0 | 0 | 0 | 0.850 | 0.134 | 0.399 | | |
| PU | ATU | 12 | 12 | 0 | 0 | 0 | 0.750 | 0.183 | 0.505 | | |
| PEOU | ATU | 11 | 10 | 1 | 0 | 0 | 0.707 | 0.178 | 0.327 | | |
| ATU | BI | 11 | 10 | 1 | 0 | 0 | 0.999 | 0.164 | 0.369 | | |
| PEOU | BI | 9 | 6 | 0 | 0 | 3 | 0.410 | 0.137 | 0.239 | | |
| PU | U | 6 | 4 | 2 | 0 | 0 | 0.670 | 0.180 | 0.443 | | |
| ATU | U | 4 | 3 | 1 | 0 | 0 | 0.400 | 0.224 | 0.331 | | |
| PEOU | U | 4 | 3 | 1 | 0 | 0 | 0.300 | 0.110 | 0.233 | | |
| BI | U | 3 | 3 | 0 | 0 | 0 | 0.545 | 0.190 | 0.365 | | |
| ANX | PEOU | 2 | 0 | 0 | 2 | 0 | | | | -0.220 | -0.530 |

According to the values in Table 3, the causal link PEOU → PU is the relationship that has been evaluated most often in existing e-learning acceptance studies. In almost all studies, a significant positive relationship between the perceived ease of use and the perceived usefulness of an e-learning technology has been demonstrated. The perceived ease of use also has a positive influence on the learner's attitude toward using an e-learning technology and the actual use of an e-learning technology. There were cases where the perceived ease of use had a negative influence on the

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learner's behavioral intentions. However, the negative influence on the learner's behavioral intentions was insignificant.

The perceived usefulness has a positive influence on a learner's behavioral intentions, attitude toward using e-learning technology and actual use of e-learning technology. The learner's actual use of an e-learning technology is also influenced by their attitude toward using the technology and behavioral intentions. Anxiety is a factor that can negatively influence a user's perceptions about the ease of use of e-learning technology.

TABLE IV. SUMMARY OF CAUSAL EFFECT SIZES (RANDOM EFFECTS MODELS)

| | PEOU → PU | PU → BI | PU → ATU | PEOU → ATU | ATU → BI | PEOU → BI | PU →U | BI → U |
|---|---|---|---|---|---|---|---|---|
| Number of samples | 25 | 17 | 12 | 10 | 10 | 6 | 3 | 3 |
| Total sample size | 6509 | 3947 | 3808 | 3233 | 3163 | 927 | 983 | 699 |
| Hedges's g | 0.928 | 0.796 | 1.240 | 0.689 | 1.594 | 0.485 | 0.933 | 0.788 |
| Standard error | 0.115 | 0.089 | 0.179 | 0.092 | 0.303 | 0.088 | 0.353 | 0.082 |
| Variance | 0.013 | 0.008 | 0.032 | 0.008 | 0.092 | 0.008 | 0.125 | 0.007 |
| Z | 8.070 | 8.915 | 6.936 | 7.494 | 5.286 | 5.526 | 0.264 | 9.587 |
| p (effect size) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.000 |
| 95% Low | 0.703 | 0.621 | 0.889 | 0.508 | 1.001 | 0.313 | 0.240 | 0.627 |
| 95% High | 1.154 | 0.971 | 1.590 | 0.869 | 2.188 | 0.657 | 1.626 | 0.950 |

Table IV shows the estimates of Hedges's g statistics for individual causal relationships. In almost all causal relationships, the effect size is medium. The effect size is relatively small only in the case of a causal relationship between the perceived ease of use and behavioral intentions. Table V summarizes the effect sizes of individual causal relationships, according to the effect size categories proposed by Kampenes et al. [7].

TABLE V. EFFECT SIZE INTERPRETATION

| | **Hedges's g** | **Interpretation** |
|---|---|---|
| PEOU → PU | 0.928 | Medium effect |
| PU → BI | 0.796 | Medium effect |
| PU → ATU | 1.240 | Large effect |
| PEOU → ATU | 0.689 | Medium effect |
| ATU → BI | 1.594 | Large effect |
| PEOU → BI | 0.485 | Medium effect |
| PU → U | 0.933 | Medium effect |
| BI → U | 0.788 | Medium effect |

The results of the meta-analysis in the field of e-learning acceptance revealed the following facts about causal relationships:

- The effect size is largest in the case of PU → ATU, and in the case of ATU → BI. The perceived usefulness also has a relatively strong influence on the actual use of an e-learning technology.
- The perceived ease of use had a relatively strong effect on perceived usefulness.
- A medium-effect size was found in ATU→BI and BI→U.

## V. CONCLUSIONS

The present meta-analysis of 28 e-learning acceptance studies involved 8,133 observations. The studies involved mostly used TAM as a ground theory for an investigation of factors that influence a learner's adoption of e-learning technology. The meta-analysis provided evidence that:

- Perceived usefulness is the strongest (direct or indirect) determinant for the learner's adoption of a specific e-learning technology.
- Perceived ease of use has a relatively small influence on a learner's intention of using a specific e-learning technology.
- The actual use of an e-learning technology is predicted by perceived usefulness and behavioral intentions.

The above-listed facts are important for different stakeholders. In particular, e-learning system developers and e-learning content providers have to improve the set of features and functionalities that will best benefit end users during their use of an e-learning technology. In our future research we will perform a qualitative-quantitative study that will help to identify which are the most useful e-learning functionalities.

In our future research, we also intend to include moderator variables (for example: user type and e-learning type). This will help us to understand if there are any other factors that have an influence on individual causal relationships.

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