

Online Learning Acceptance Model during Covid-19: An Integrated Conceptual Model

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Abstract—Because of Covid-19, many countries shutdown schools in order to prevent spreading the virus in their communities. Therefore, schools have opted to use online learning technologies that support distance learning for students. As consequences, Ministry of Higher Education and Scientific Research encourages higher education institutes to adopt blended learning in their programs. However, different students react in different ways to online learning. Some students were able to make productive use of online learning strategies more than others. A conceptual model based on 15 variables was constructed based on UTAUT2, TAM, and other models to investigate and to study the factors that affect students' acceptance of online learning. 29 hypotheses were investigated to study the relationships among the variables that affect online learning acceptance and online learning community building in Al-Ahliyya Amman University. The collected responses were analyzed using a structural equation modeling (SEM) approach. SPSS and AMOS were used to analyze the data.

Keywords—Online learning; technology acceptance; learning assistance; learning community building assistance

I. INTRODUCTION

Since Covid-19 (Coronavirus) started spreading, many countries decided to shutdown schools and move to online learning solutions [1, 2]. Moving to distance learning because of the virus became necessary in order to keep providing education to students. Different distance learning paradigms were implemented to support distance learning such as live-streaming lectures [3], the use of Massive Open Online Courses (MOOC) [4], and the use of worksheets and animations [5]. Additionally, some educational gamification [6, 7] websites and computer applications were adapted to support online learning. Unfortunately, not all students accept the online learning in place of face-to-face classes.

Based on the online learning feedback during Covid-19, Ministry of Higher Education and Scientific Research developed a plan to adopt online and blended learning in the higher education institutes. As consequences a three-year action plan (2021-2023) was developed to manage adapting synchronized and asynchronized online learning to be blended in higher education. The plan included training faculty members from private and public university. However, moving from traditional lecture-led classes to online learning would cause to move from lecture-centric to learning-centric

paradigms. Therefore, students need also to be training and to adapt to the new learning paradigms.

Although the members of Generation Z, who are familiar with various technologies accessing the internet, are the majority of students, it is very important to study the factors that affect their intention to use their technical knowledge in digital learning [8]. It is very important to know the factors that are affecting users' adoption of technologies in order to achieve the objectives of the proposed technology. Many models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) [9, 10], were proposed to explain users' behavior in utilizing technologies. However, the factors that affect the use of a technology are vary based on the environment [11].

In this research, a model is constructed using 15 variables to investigate its effects on the online learning in Al-Ahliyya Amman University. The model was developed based on UTAUT2 [10], the conceptual TAM (Technology Acceptance Model) [12-15], and a conceptual model proposed by Vululleh [16]. Based on the defined variables, the research model was constructed, and 29 hypotheses were investigated and analyzed using a structural equation modeling (SEM) approach in SPSS and AMOS.

II. LITERATURE REVIEW

One of the widely applied models to study the factors that affect using a technology is UTAUT [9]. It was developed by investigating eight different models. The eight models are the model of PC utilization (MPCU) [17], social cognitive theory (SCT) [18], Technology Acceptance Model (TAM) [19], innovation diffusion theory (IDT) [20], the combined theory of planned behavior/technology acceptance model (C-TPB-TAM) [21], and the motivational model (MM) [22]. As a result, UTAUT was formulated based on four factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Also, UTAUT considered four moderators: gender, age, experience, and voluntariness of use. In 2012, UTAUT was extended to UTAUT2 [10] by adding hedonic motivation, price value, and habit factors to the model. Later, the Values-Enhanced Technology Adoption (VETA) model [23] extended UTAUT2 by adding new variables to UTAUT2 variables. Although UTAUT and UTAUT2 are widely used to study the acceptance of technology, they need to be adapted to the context of eLearning.

Islam [13] investigates the effects of learning management systems (LMS) on achieving learning outcomes by developing a model based on TAM. The model suggests that LMS may assist students in learning and building a collaborative network in hybrid courses which combine both face-to-face education and online learning. Learning assistance and perceived community building assistance were added to TAM. The model was formulated using five factors: Perceived Usefulness, Perceived Ease of Use, e-Learning Use, Perceived Learning Assistance, and Perceived Community Building Assistance. The model did not consider the design of online courses nor the factors which can affect the learner community building.

Since online learning is usually web browser-based or based in mobile applications, a model developed by Liu, et al. [12] added new variables that may affect the acceptance of online learning to TAM. The new variables are related to the technology design and the user experience with technology. The model used the following constructs: Perceived Usefulness, Perceived Ease of Use, and Intension to Use (from TAM). The following constructs were developed: Online Course Design, User-Interface Design, Previous Online Learning Experience, and Perceived Interaction. The model integrates the effects of online course design and interface design with TAM. However, the model did not consider the effects of the variables such as hedonic motivation, price value, community building and habit factors.

Vululleh [16] studied students' acceptance of e-learning technology in Liberia. The research model was based on TAM, which proposes that users' Behavioral Intention to adopt a technology is controlled by their beliefs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Additionally, the model extended TAM by adding two factors, Social Influence (SI) and Quality of Life (QL). Therefore, the conceptual model studied the effects of four factors: PU, PEOU, SI, and QL on the Behavior Intention (BI) to use e-learning. Like Liu, et al. [12] and Islam [13], Vululleh [16] proposed a model based on TAM. Factors such as design, interface and community building were not considered.

Some models studied the differences of acceptance in different environment. For instance, Lee [14] examines the difference between Korean and American students' perceptions of online education. The model was based on TAM using the two factors Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), and adding the two factors Perception of Online Learning Acceptance and Student Satisfaction (OLAS) and Online Education Support Service Quality (PSQ). The model found that the (PSQ) directly influenced behavioral intention toward online learning acceptance and student satisfaction. However, the impact of service quality on the behavioral intension toward e-learning in different cultures was limited. The model investigates the direct and indirect effects of PSQ on PLAS; however, more variables such as design, interface and community building need to be considered.

The model proposed by Ratna and Mehra [15] examines the behavioral intention of the university students in India for using e-learning. The model was based on TAM using the

factors of Gender, Student Major, and Monthly Family Income. It examines the applicability of TAM among university students in India and found that Perceived Ease of Use (PEOU) has a significant effect on Perceived Usefulness (PU), Attitude (ATT), Behavioral Intention (BI) and Actual Use (AU). Also, PU has a significant effect on ATT, BI, and AU. Moreover, ATT has a significant effect on Intention to Use (INT). Finally, this model found that BI has a significant effect on AU. Like the aforementioned models, this model is also based on TAM and limited to study the effects of four variables only.

III. MODEL DEVELOPMENT

The proposed model is based on 15 variables that were utilized in several studies [9, 10, 12-16, 19, 24, 25] to investigate the factors that affect the adoption of technologies:

1) Performance Expectancy is how technology benefits users to perform certain activities [10], and Perceived Learning Assistance (PLA) is how an online learning component can help the individual's learning [13]. Therefore, in our research model, these two factors are combined into one factor.

2) Perceived Community Building Assistance (PCBA) refers how the online learning helps individuals to have social interactions with others [13]. Liu, et al. [12] defines Perceived Interaction as interpersonal interaction and human-system interaction. The interpersonal interactions include interactions with peers and instructors. In our conceptual model, we opt to include Perceived Community Building Assistance and interpersonal interaction into one factor.

3) Online Course Design (OCD) refers to the types and quality of the materials that can be included in the online course [12]. Since the online course is web browser-based or based in a mobile application, it can include different types of material such as images, animation, and video. Therefore, the quality of these materials can have great impact on users.

4) When developing software, User-Interface Design (UID) plays crucial role in the success of the software. In online course, User-Interface Design refers the organization and arrangement of the online course content and visual design [12].

5) Effort Expectancy is how ease the use of the technology affects users [10]. Effort Expectancy is also called by other researchers such as Liu, et al. [12] as Perceived Ease of Use. Hence, only one of them (PEU) is included in our conceptual model to find the effects of ease of use of e-learning technology on the intention to use it.

6) Social Influence (SI) is how other people, such as family and friends, influence users' decisions to adopt the technology [10].

7) Facilitating Conditions are the resources and the support that are available to the user to use the technology [9]. These include both physical and environmental factors [26] that help students to learn using online resources. In our model, the Perceived Service Quality (PSQ) variable represents all the factors that help the students to use the online resources.

8) Hedonic Motivation (HM) is defined as the fun, enjoyment, or pleasure that the users of a technology can have [10]. This variable was not in UTAUT [9], but it was added to UTAUT2 [10] and was considered the most important added variable to UTAUT2 [27].

9) Quality of Life (QoL) is how online learning processes can affect the students' faith [26]. This includes saving time and costs when using or downloading the online learning materials.

10) Price Value (PV) is the monetary costs assigned with the use of the technology [10].

11) Habit and Experience (Habit) is the user's ability to use the technology without the need for training because of learning and previous experience [10].

12) Behavioral Intention (BI) measures students' acceptance of online courses in the present and in the future [26].

13) Technological Experience (EXP) represents the skills that students need to use online courses. Martinho, et al. [24] classify Technological Experience into two external variables: Base Technological Experience and Advanced Technological Experience. However, since basic computer skills are taught in schools starting from the elementary grades, we opt in the proposed model not to distinguish between Base Technological Experience and Advanced Technological Experience.

14) Perceived Usefulness (PU) is the degree to which students believe that online learning will enhance their job performance [13]. This variable was introduced in TAM [19].

15) Previous Online Learning Experience (OLE) [12] including using technology, internet, and online learning resources can affect learners' intentions to use online learning.

Based on the aforementioned variables, the following hypotheses were proposed.

H1: OLE will positively affect students' BI to use online courses.

H2: OLE will positively affect students' PU of online courses.

H3: OLE will positively affect students' PEU of online courses.

H4: OCD will positively affect students' PU of online courses.

H5: OCD will positively affect students' PEU of online courses.

H6: OCD will positively affect students' PCBA of online courses.

H7: PSQ will positively affect students' PU of online courses.

H8: PSQ will positively affect students' BI to use online courses.

H9: PSQ will positively affect students' PEU of online courses.

H10: UID will positively affect students' PEU of online courses.

H11: UID will positively affect students' PCBA of online courses.

H12: PU of online courses will positively affect students' BI to use online courses.

H13: PU of online courses will positively affect students' PLA to use online courses.

H14: PU of online courses will positively affect students' PCBA of online courses.

H15: EXP will positively affect students' PU of online courses.

H16: EXP will positively affect students' PEU of online courses.

H17: PEU of online courses will positively affect students' PU of online courses.

H18: PEU of online courses will positively affect students' BI to use online courses.

H19: PEU of online courses will positively affect students' PLA to use online courses.

H20: PEU of online courses will positively affect students' PCBA of online courses.

H21: SI will positively affect students' PU of online courses.

H22: SI will positively affect students' BI to use online courses.

H23: BI to use online courses will positively affect students' PLA to use online courses.

H24: BI to use online courses will positively affect students' PCBA of online courses.

H25: QoL will positively affect students' BI to use online courses.

H26: HM will positively affect students' BI to use online courses.

H27: PV will positively affect students' BI to use online courses.

H28: Habit will positively affect students' BI to use online courses.

H29: PCBA will positively affect students' PLA to use online courses.

IV. METHODOLOGY

Quantitative methods were utilized, in the form of non-structured survey questionnaires with closed questions using a 5-point Likert-type scale where 1 is highly disagree and 5 is highly agree. The questionnaire was constructed of 15 variables and 69 items in total. The items included in the questionnaire were collected from prior studies. Prior to the survey, a pilot study was conducted to assure the reliability and

validity of the questionnaire. The entire instrument demonstrated acceptable reliability; Cronbach's alpha was 0.962. The questionnaire was randomly distributed to Al-Ahliyya Amman University students. The final accepted questionnaires for analysis were 462 out of 517 from the submitted responses. The data were analyzed using SPSS version 25 and AMOS version 23.

A. Data Analysis

There are nine colleges in Al-Ahliyya Amman University: Faculty of Information Technology, Faculty of Pharmacy, Faculty of Architecture & Design, Faculty of Allied Medical Sciences, Faculty of Arts & Sciences, Faculty of Engineering, Business School, Faculty of Law, and Faculty of Nursing. The responses, which were used in the analysis according to the colleges, was as followings: Faculty of Information Technology (36%), Business School (22.7%), Faculty of Pharmacy (19%), and the other colleges (22.3%) (see Table 1).

Faculty of Engineering and Faculty of Pharmacy are five-year colleges, while the other colleges are four-year colleges. The responses that were used spanned the following student levels: First Year (24%), Second Year (25.8%), Third Year (21.6%), Fourth Year (17.7%), and Fifth Year (10.8%) (see Table 2).

Table 3 illustrates the previous student experience with online courses. 60 students (13%) had never ever studied with any online course, while 402 (87%) students had studied using some online courses. 205 students studied one or two online courses. 165 students studied 3 to 5 online courses. 32 students studied 6 or more online courses.

TABLE I. STUDENT DISTRIBUTION OVER COLLEGES

College	Frequency	Percent
Faculty of Information Technology	167	36.1
Faculty of Pharmacy	88	19.0
Faculty of Architecture & Design	21	4.5
Faculty of Allied Medical Sciences	13	2.8
Faculty of Arts & Sciences	24	5.2
Faculty of Engineering	19	4.1
Business School	105	22.7
Faculty of Law	18	3.9
Faculty of Nursing	7	1.5
Total	462	100.0

TABLE II. STUDENT LEVELS

Level	Frequency	Percent
First Year	111	24.0
Second Year	119	25.8
Third Year	100	21.6
Fourth Year	82	17.7
Fifth Year	50	10.8
Total	462	100.0

TABLE III. STUDENT EXPERIENCE WITH ONLINE COURSES

Online Course	Frequency	Percent
Never studied online course	60	13.0
studied 1-2 online courses	205	44.4
studied 3-5 online courses	165	35.7
Studied more than 6 online courses	32	6.9
Total	462	100.0

B. Hypotheses Testing

The model is consisted of 15 variables that were measured in a questionnaire of 69 items. The variable averages (ranging from 3.5 to 3.9) and standard deviations (ranging from 1 to 1.3) are listed in Table 4. The variables Cronbach's Alpha if Item Deleted was ranged from 0.958 and 0.962. Since total variable Cronbach's Alpha is 0.962, all variables were included in the model and none of them need to be dropped. Many indexes were measured to test the model fitness (see Table 5). Since all the minimum values of the indexes were achieved, the model fits enough to measure the hypotheses. All factor loadings were above 0.6; therefore, all items were used in the analysis.

TABLE IV. THE MODEL VARIABLES

Variable	Mean	Std. Deviation	Cronbach's Alpha if Item Deleted
PU	3.4654	1.04352	.959
PEU	3.4802	1.04912	.959
PLA	3.5415	1.13455	.959
PSQ	3.5584	1.12182	.958
EXP	3.9446	1.24697	.960
PCBA	3.5361	1.10217	.958
OCD	3.5000	1.16716	.958
UID	3.5260	1.24651	.958
OLE	3.6075	1.25583	.959
SI	3.5216	1.14455	.958
QoL	3.5628	1.18976	.958
BIs	3.6129	1.17900	.958
PV	3.4726	1.19596	.962
Habit	3.5476	1.07761	.959
HM	3.5440	1.29309	.960

TABLE V. MODEL FIT RESULTS

Index	Value	Recommended values
Degrees of freedom	2203	> 0 [17]
Discrepancy Chi-Squared	4031	> .05 [17]
Relative Chi-Squared	1.83	< 5.0 [18]
Comparative Fit Index	0.915	≥ 0.9 [18, 19]
Tucker Lewis Index	0.909	≥ 0.9 [17, 20]
Incremental Fit Index	0.915	≥ 0.9 [17, 20]
Root Mean Square of Error Approximation	0.042	≤ 0.08 [17]

The 29 hypotheses were tested using AMOS. 15 hypotheses were supported while 14 hypotheses were rejected. The result is illustrated in Table 6. H17, which states that Perceived Ease of Use of online courses will positively affect students' Perceived Usefulness of online courses, has high impacts; if Perceived Ease of Use goes up by 1 unit, Perceived Usefulness of online courses goes up by 1.204. In addition, if Perceived Ease of Use goes up by 1 unit, PLA goes up by 0.839 unit. Therefore, Perceived Ease of Use is considered a very important factor in online learning.

On the other hand, the effects of the factors in H7, H14, and H18 have negative effects. In H18, Perceived Ease of Use will negatively affect Behavioral Intentions. When Perceived Ease

of Use goes up one-unit, Behavioral Intentions goes down by 0.822. Thus, when the students feel that online courses are too easy to use, they will use them less. In short, H7, H14, and H18 will be stated as following:

H7: Perceived Service Quality negatively affects students' Perceived Usefulness of online courses.

H14: Perceived Usefulness of online courses negatively affects students' Community Building Assistance of online courses.

H18: Perceived Ease of Use of online courses negatively affects students' Behavior Intention to use online.

TABLE VI. HYPOTHESES TESTING

Hypotheses				Estimated	S.E.	C.R.	P	Comments
H1	BI	←	OLE	-0.076	0.089	-0.858	0.391	Not Supported
H2	PU	←	OLE	0.041	0.074	0.559	0.576	Not Supported
H3	PEU	←	OLE	0.003	0.055	0.054	0.957	Not Supported
H4	PU	←	OCD	0.25	0.096	2.595	0.009	Supported*
H5	PEU	←	OCD	0.332	0.109	3.057	0.002	Supported*
H6	PCBA	←	OCD	0.684	0.169	4.034	***	Supported***
H7	PU	←	PSQ	-0.368	0.143	-2.582	0.01	Supported**
H8	BI	←	PSQ	0.362	0.193	1.87	0.062	Not Supported
H9	PEU	←	PSQ	0.63	0.09	6.969	***	Supported***
H10	PEU	←	UID	-0.12	0.086	-1.404	0.16	Not Supported
H11	PCBA	←	UID	-0.162	0.109	-1.484	0.138	Not Supported
H12	BI	←	PU	0.565	0.243	2.33	0.02	Supported*
H13	PLA	←	PU	0.034	0.137	0.248	0.804	Not Supported
H14	PCBA	←	PU	-0.286	0.141	-2.025	0.043	Supported*
H15	PU	←	EXP	-0.013	0.045	-0.286	0.775	Not Supported
H16	PEU	←	EXP	-0.012	0.043	-0.278	0.781	Not Supported
H17	PU	←	PEU	1.204	0.18	6.674	***	Supported***
H18	BI	←	PEU	-0.822	0.401	-2.052	0.04	Supported*
H19	PLA	←	PEU	0.839	0.183	4.586	***	Supported***
H20	PCBA	←	PEU	0.653	0.165	3.963	***	Supported***
H21	PU	←	SI	-0.142	0.095	-1.497	0.134	Not Supported
H22	BI	←	SI	0.377	0.122	3.095	0.002	Supported**
H23	PLA	←	BI	0.222	0.052	4.273	***	Supported***
H24	PCBA	←	BI	0.059	0.066	0.892	0.373	Not Supported
H25	BI	←	QoL	0.388	0.085	4.589	***	Supported***
H26	BI	←	HM	0.023	0.048	0.48	0.631	Not Supported
H27	BI	←	PV	-0.073	0.046	-1.605	0.109	Not Supported
H28	BI	←	Habit	0.315	0.076	4.165	***	Supported***
H29	PLA	←	PCBA	-0.041	0.082	-0.496	0.62	Not Supported

*** Significant $p \leq 0.001$, ** Significant $p \leq 0.01$, * Significant $p \leq 0.05$

V. LIMITATION AND CONCLUSION

The study was conducted in a private university, Al-Ahliyya Amman University. Online learning has become a necessity after the spread of Covid-19. Therefore, this study can be extended to include responses from students in different educational institutions, including public and private institutions and K-12 institutions. All responses were collected from students. The study can be extended to collect responses from instructors as well. Finally, the moderator affects, such as age, gender, and experience, were not considered in this study because there studies such as Liao, et al. [21] and Kharna [22] found that there were no significant effects of these moderators in online learning models. However, when extending the study to include different categories of educational institutions, there might be impacts of these moderators on the relations in the model.

The study proposed a theoretical model to investigate the effects of 15 variables on online learning acceptance. Based on these 15 variables, 29 hypotheses were tested. Only 14 hypotheses were supported. The final model is shown in Fig 1.

Four variables: Perceived Usefulness, Social Influence, Quality of Life, and Habit had positive effects on Behavioral Intention to use the online course. The highest estimated beta value of these was of Perceived Usefulness. In other words, in order to increase students' behavioral intention to use an online course, they should know the importance of the online courses in learning. The role of academic advising can help in increasing students' awareness of the usefulness of online learning and how it can affect the learning process by accessing the online material at anytime and anywhere.

Moreover, the study found that the course design and ease of use of the course affect the online collaborative learning. Therefore, in order to enhance peer-learning and group-learning, the online courses should include in the design simple and easy features that allow students to communicate with their classmates. Additionally, ease of use positively affects students' perceptions of online learning. Hence, the ease of use of online learning components and environment is crucial to increasing students' intent to learn from online learning components and to cooperate with their classmates.

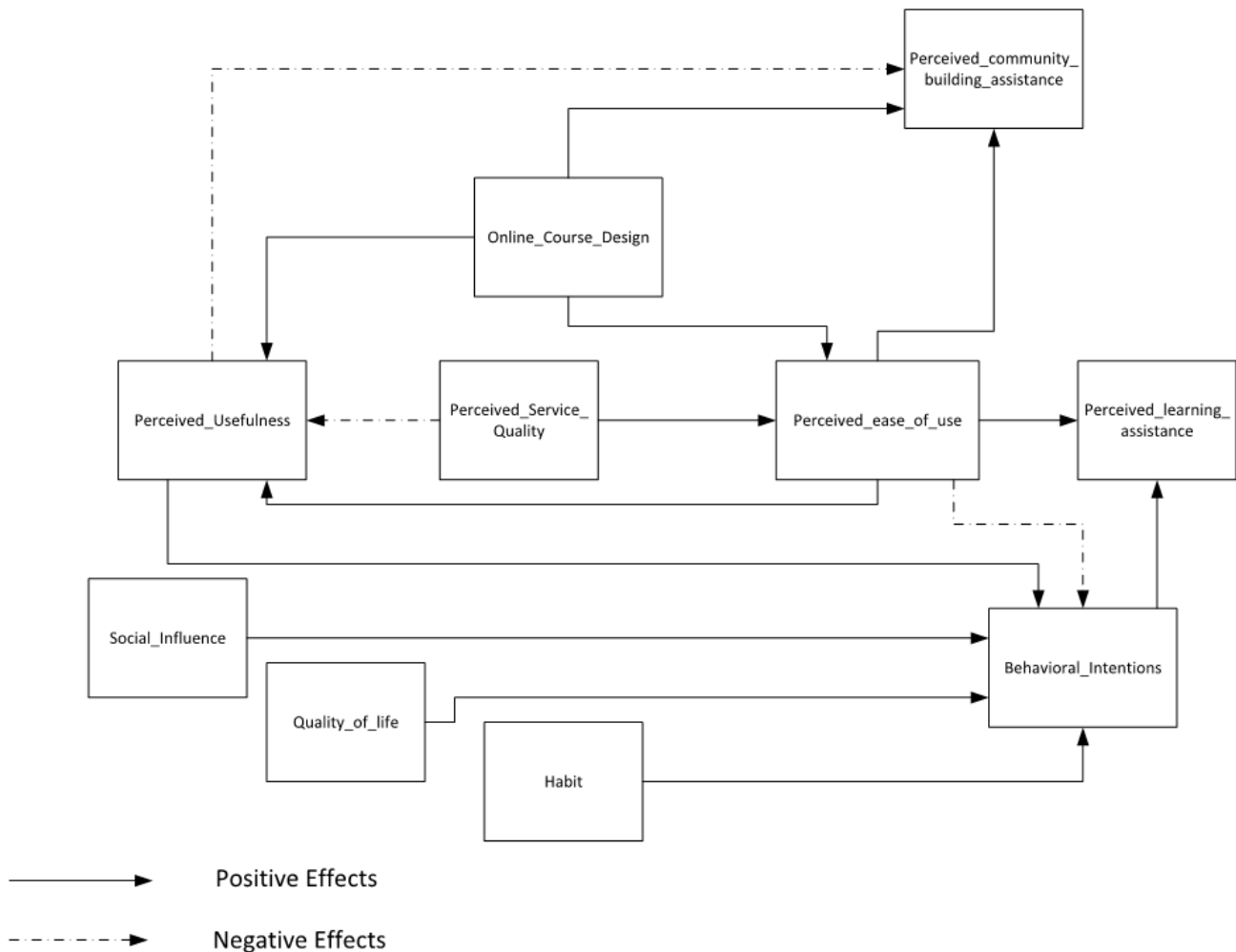


Fig. 1. Final Model.

Three relations had negative effects in the model. The first one is that the more assistance in using the online course, and more physical requirements to access the online course, the less usefulness the online course has. The second is that the more assistance in using the online course and more physical requirements to access the online course, the less collaboration there is with others. Finally, if the students feel that the online course is too easy, they won't be as interested in the online course. Therefore, the physical requirements and the technical assistance should be minimized. For instance, online courses should use good compression to minimize the usage of internet bandwidth and hardware requirements. Additionally, online courses should not be too easy. The students like some challenges in the learning process.

Finally, the effects of Hedonic Motivation were not supported. This finding agrees with Mehta, et al. [23]. College-level students do not use online learning for fun. However, further investigation is needed to study the effects of Hedonic Motivation in different educational system levels, such as K-12 schools.

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