Determinants of Intention to use Google Lens

Vinh T. Nguyen
TNU – University of Information and Communication Technology, Viet Nam
http://orcid.org/0000-0002-1300-3943

***Abstract*—The Covid-19 epidemic has had a tremendous impact on all sectors of life. Children have more time to explore their environment and ask difficult questions that cannot be addressed instantly by their parents or relatives. Google Lens might be regarded as a useful auxiliary tool in addressing this issue. This study looked at the effects of seven different factors on people's intentions to use Google Lens. The modified Unified Theory of Acceptance and Use of Technology model was used to assess user behavior. Generalized structured component analysis was employed to evaluate the proposed study model. Using data of 395 participants who had kids at home due to social distancing, the study results showed that performance expectancy, utilitarian value, social influence had a statistically significant and positive impact on behavioral intention, perceived risk had a statistically significant and negative effect on behavioral intention. However, this study did not find significant relationships between the effort expectancy and the behavioral intention, nor between the hedonic motivation and the intention to use the Google Lens application. Due to the dissatisfaction with validity and consistency, the factor of facilitating conditions was not included in the analysis. The reasons for these non-significant correlations will be examined further in a large-scale user experience research.**

***Index Terms*— Google Lens; Augmented Reality; UTAUT; Covid-19; GSCA; perceived risk**

I. Introduction

The outbreak of the Covid-19 pandemic has had a profound effect on all aspects of life. The social distancing has forced organizations and companies to change their working strategies to adapt with the "new normal" [2]. The field of education is also not out of the influence when schools must switch from traditional teaching models to online teaching [3]. Students at the pre-school and primary levels are not allowed to go to school and must study on their own in many countries. While not attending schools, children have more time to explore their surroundings and ask challenging questions that cannot be answered immediately by their parents or relatives.

For example, "what is the name of this leaf? What is it used for?" or "Grandpa, what are the English's names of these animals?". Giving a concise answer for this type of questions may be difficult for many parents or adults when these subjects are not of their expertise.

The presence of Google Lens in the last few years is expected to alleviate the above issue and the like. Google Lens [4] is a Google image recognition system (see Fig. 1) that uses visual analysis based on a neural network to bring up relevant information about things it recognizes. Google Lens attempts to identify the object by scanning barcodes, QR codes, labeling and text when directing the phone camera onto an object, and shows the corresponding search results, web pages and information. It was first announced during Google I/O 2017, but until June 2018 it was released as a standalone Google Lens apps available on Google Play. After three years of development, the app was downloaded more than 500 million times. Currently, Google Lens supports six features including: 1) scan and translate text - translating words, saving business cards, adding up events from a poster to one's calendar, and copying and pasting complex and time-consuming codes or large phrases into one's telephone, 2) identify plants and animals – finding out what the plant was in the new places or what kind of dog you spotted in the park, 3) explore places around you – identifying and learning about sites, restaurants, and shops, seeing ratings, operating times, or historical information of attractions, 4) find the look you like – finding out whether an object fits to your home or clothes match your body, 5) know what to order – seeing a menu of popular foods based on Google Maps evaluation, and 6) scan codes – QR codes and barcodes are quickly scanned to extract data and get information. More than one billion questions have been asked on Google Lens [7].

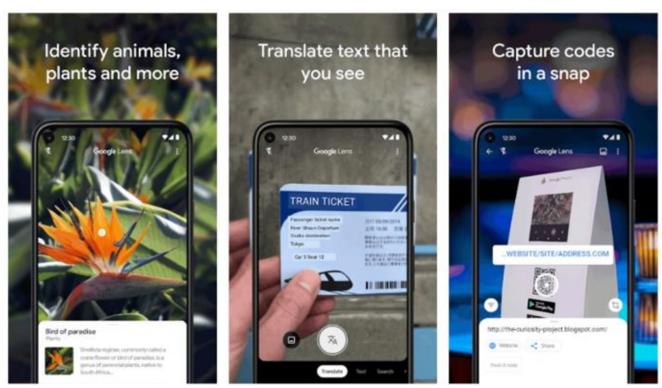

Fig. 1 Google Lens' features. Source: internet

The marriage of Artificial Intelligence (AI) with augmented

Vinh T. Nguyen is with TNU – University of Information and Communication Technology, Thai Nguyen, Vietnam (email: vinhnt@ictu.edu.vn)

Vinh T. Nguyen is also with FPT University, Hanoi, Vietnam (email: vinhnt56@fe.edu.vn)

reality (AR) is a unique and multifaceted development for portable devices, not only in the gaming sector but also in the educational arena. Although research interests in AI and AR have risen in the past, few studies have investigated them both in the context of children explorations with mobile devices. Only a little amount of study has been conducted to investigate the possibility of utilizing Google Lens in identifying objects [9-11], thus remain an open gap in the literature.

This work addresses the above research gap by introducing these research questions: (R1) to what extent a performance factor, an effort factor, a social factor, and a facilitating condition factor can predict behavioral intention? (R2) to what extent hedonic, and utilitarian values can predict behavioral intention? and (R3) to what extent a risk factor can predict hedonic, and utilitarian values? This paper contributes scarce research on Artificial Intelligence - Augmented Reality on mobile devices by expanding the application of the unified theory of acceptance and use of technology (UTAUT) in the context of children learning at home during the Covid-19 pandemic, adding three new external factors such as perceived risk, hedonic, and utilitarian values.

The rest of this article is organized as follows: Section II will briefly review existing studies that is closed to our work. The materials and methods section will describe data and analytical methods. Section IV results will report findings with some discussions. The article is concluded in Section V.

II. LITERATURE REVIEW

In the literature, the possibility of employing Google Lens in education has been examined [10]. The authors reported that Google Lens can increase student’s enthusiasm to learn and correlate to STEM education trends. However, the usage of this tool is hampered by a variety of issues, including instructors' lack of understanding of the system, a lack of advice on how to use the application, and the unavailability of the majority of foreign-language interfaces. When applying to a specific context, it was discovered that Google Lens has a very high accuracy of identification, particularly on trees and plants [11]. In line with this research, the authors extended the studies by comparing Google Lens with several other applications [12]. Their results showed that the most useful and informative interface of plant identification applications is Flora Incognita and PlantNet. However, the accuracy compared to Google Lens findings was much lower. A further comparison of user friendliness of applications showed that Google Lens is the most useful tool for plant identification during biology lectures.

By using Google Lens as a case study, Lucia et al. [13] investigated the consequences of altered set of spatial, gestural and cognitive relations in order to better understand how locative media may impact everyday users' interactions and experiences with their surroundings. They argued that the application advances reductive representations of complicated sets of relationships formed by locative media and augmented reality. Locative media, in this sense, is defined as the media linked to a given geographical location. Viswanadhuni et al. [14] proposed a domain knowledge embedding model as a content provider for AI camera solution (e.g., Google Lens, Bixby Vision). The output of this model aids in obtaining appropriate information from the content provider. Their research Intent Classification model predicted three types of intents with 91 percent accuracy including beauty product purchase interest, generic information seeking, and movie information seeking intents.

Sergeeva et al. [15] examined the possibility of utilizing Augmented Reality in teaching foreign language. Forty students took part in VR/AR course introducing AR tools (e.g., Google Lens, AR browsers, and WallaMe service). Their studies reported that AR can be applied in foreign language classes as it contributed to the optimization of the educational process by filling it with information, involving students, and successfully influencing the process of developing the student's foreign language competency. In addition, Google Lens is also used flexibly in some cases. For example, Rebekah et al. [16] utilized Google Lens as a means to count the number of employees based on the facial detection feature of Google Lens. The corresponding image frames of the detected person were kept extracting desirable features such as ID card and Shoe. Or Kumar et al. [17] utilized Google Lens to split the text from the image, which was then processed as independent entities and delivered to the text and image analytics modules.

III. MATERIALS AND METHODS

A. Conceptual Framework and Research Hypotheses

Many apps and software have been developed since the invention of computers to assist users in improving job productivity, reducing computation time, and optimizing manufacturing and commercial operations. However, not every software lives up to its initial aspirations. If the application's development and market are not correctly planned, the manufacturer will suffer greatly in terms of labor charges, operational costs, advertising costs, and so on. To mitigate the aforementioned risks, researchers have proposed several alternative models for attitude, behavior, satisfaction, and user acceptance prior to the release of advertising software on the market. The Technology Acceptance Model (TAM) is such a model being widely used in the literature to predict the user’s acceptability for an information technology system [18]. The TAM model consists of four major factors: actual system usage, behavioral intention, perceived usefulness, and perceived ease of use. According to TAM, when consumers are introduced to a new technology, the perceived usefulness and ease of use of the technology have a direct effect on behavioral intentions and an indirect influence on actual software usage. Over time, the TAM model was further developed by including variables such as subjective norm, image, job relevance, output quality, result demonstrability, visual design, and task technology fit. The availability of several models and the introduction of numerous additional variables have caused significant difficulties for researchers not specializing in social behavior. To overcome the issue, the Unified Theory of Acceptance and Use of Technology (UTAUT) model came up when eight prior models were combined and refined into one single model to explain user behavior with an IT system [1]. According to the author, four key elements impact user behavior, including: performance expectancy, effort expectancy, social influence and facilitating conditions. In this study, we extend the UTAUT model with three new factors: perceived risk, hedonic, and utilitarian values.

Behavioral Intention: The great majority of behavioral theories and models such as the TAM, Reasoned Action Theory (TRA), or UTAUT aim at examining the variables impacting consumers to embrace the technology [19]. Behavioral intention was defined as "a person's subjective probability that he/she will perform some behavior" [20]. In the context of this study, the behavioral intention is defined as the likelihood that a person will use Google Lens in learning. Three questions were used to assess behavioral intention including: 1) I intend to use Google Lens in the next six months for teaching/learning, 2) I predict I will use Google Lens in the next six months, 3) I plan to use Google Lens each time I need it for teaching/learning.

Performance Expectancy: Performance Expectancy is defined as an individual's belief that using the system will help them achieve their job performance goals [1]. Perceived usefulness, extrinsic motivation, job fit, relative advantage, and outcome expectations are five factors from various models related to performance expectations [1]. In this study, we use three questions to assess performance expectancy: 1) I would find Google Lens useful for my teaching/learning, 2) I think using Google Lens will enhance productivity in my job, 3) I think using Google Lens will help me save searching time with the following hypothesis:

Hypothesis 1 (H1). **Performance expectancy has a positive effect on behavioral intention.**

Effort Expectancy: Effort Expectancy is defined as the ease with which the system can be used [1], it is a crucial predictor in the UTAUT model. Perceived ease of use, complexity, and ease of use are three factors from distinct models associated to effort expectations. In the context of this study, effort expectancy represents users' beliefs regarding the ease of use of Google Lens. We used four questions to assess effort expectancy, which are as follows: 1) I would find Google Lens easy to use, 2) I would not take me long to learn how to use Google Lens, 3) My interaction with Google Lens would be clear and understandable, and 4) It would be easy for me to become skillful at using Google Lens with the following hypothesis:

Hypothesis 2 (H2). Effort expectancy has a positive effect on behavioral intention

Social Influence: The degree to which a person believes that important individuals feel he or she should utilize a specific technology is described as social influence [1]. According to UTAUT, social influence has a direct beneficial effect on behavioral intention since it changes potential users' attitudes. In the context of this study, social influence refers to friends, family members, colleagues who influence an individual to use a new technology. We used four questions to assess effort expectancy, which are as follows: 1) People who influence my behavior think that I should use Google Lens for my daily jobs, 2) I think I am more likely to use Google Lens if my friends and my family use it, and 3) I use Google Lens because of my colleagues who use the application with the following hypothesis:

Hypothesis 3 (H3). Social influence has a positive influence on behavioral intention.

Facilitating Condition: The degree to which a person feels that an organizational and technological infrastructure exists to facilitate the usage of the system is described as facilitating conditions [1]. In this study, we used four questions to assess effort expectancy, which are as follows: 1) I have the resources necessary to use Google Lens, 2) I have the knowledge necessary to use Google Lens, 3) Google Lens is compatible with my devices, and 4) If I have problem using Google Lens, I can get help from the service provider with the following hypothesis:

Hypothesis 4 (H4). Facilitating conditions have a positive effect on behavioral intention.

Hedonic Motivation: Hedonic motivation is defined as the desire to accomplish something for the sake of interior fulfillment [5]. The hedonic motivation is linked to the core emotions and psychological experiences of each individual, which may both be activated by the individual characteristics and cognitive conditions. In other words, an individual's hedonic experiences with a technological product such as a Google Lens makes them more likely to engage in experimental behavior. In this study, we used four questions to assess hedonic motivation, which are as follows: 1) I think using Google Lens is fun, 2) I think using Google Lens is entertaining, and 3) I think using Google Lens is enjoyable with the following hypothesis:

Hypothesis 5 (H5). Hedonic motivations have a positive effect on behavioral intention.

Utilitarian Value: Utilitarian value is defined as the value received by a consumer as a result of task-related and rational consuming behavior [6]. In the context of this study, utilitarian value refers to the features that Google Lens supports to accelerate teaching/learning. The greater the value of the benefits gained by consumers via Google Lens, the more pleased customers will be. We used three questions to assess utilitarian value, which are as follows: 1) I find it easy to get the Google Lens features to do what I want to do, 2) The provided features on Google Lens helped me better finding information, and 3) Using the features on Google Lens enables me to accelerate teaching/learning with the following hypothesis:

Hypothesis 6 (H6). Utilitarian Values have a positive effect on behavioral intention.

Perceived Risk: Featherman and Pavlou [8] defined perceived risk as the "potential for loss in the pursuit of a desired outcome of using an e-service." In this study, perceived risk is defined as the likelihood of a person suffering a loss of using Google Lens. The lower the customer's Perceived Risk, the higher their level of contentment. We used four questions to assess perceived risk, which are as follows: 1) I think using Google Lens puts my privacy at risk, 2) Using Google Lens exposes me to an overall risk, and 3) Using Google Lens will not fit well with my self-image with the following hypothesis:

Hypothesis 7 (H7). Perceived risks have a negative effect on behavioral intention.

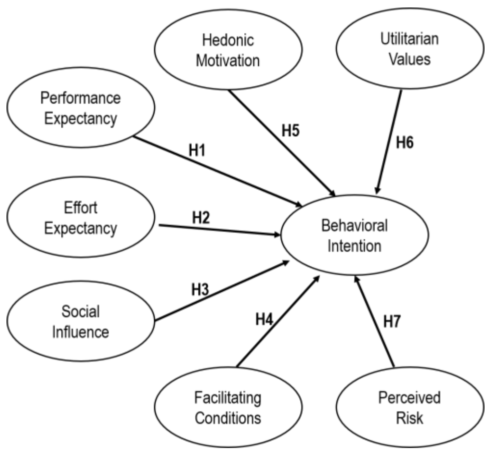

Fig. 2 The proposed conceptual model

B. Participants and Data Collection

In order to acquire data, the study used a non-probability, purposive sampling technique. The online survey was created and administered to participants through Google Form. An invitation letter was sent to users via email and social network channel (e.g., Facebook, Twitter) along with the Google Form link. Participants of interests are those who have kids forcing to stay at home due to Covid-19. Thus, the estimated number of users participating in the study was 730 participants through snowball sampling technique, the response rate is 452 (61.91%). The survey consisted of two parts: (a) four questions to acquire demographic information, (b) 26 Likert-type questions for different points of view using Google Lens. After data were collected, the research team removed inappropriate responses (i.e., 45 invalid answers due to selecting only one option – that is option 5 for all responses, 12 responses due to missing values). The final total data for inclusion in the analysis were 395 (87.39%).

The sample size is a controversial issue in the literature. If there is insufficient data, the model will not be able to converge. As a result, the outcome is insecure and untrustworthy. When there is an abundance of data, the power of statistics, i.e., constructing a population inference from sampling, cannot be employed. When all of the data (i.e., the population) is gathered, there is no need for an inferential approach because all of the data is accessible. Consequently, the sample size determination in the literature is varied to date. Some researchers are in favor of a minimum sample size 100-200 each study [21]. The sample size suitable to the test may vary from 300 to 500 [21], or with criteria that are acceptable for five samples per free parameter. Anderson and Gerbing [22] contended that when there are three or more indicators per factor, a sample size of 100 is generally adequate for convergence, and a sample size of 150 is usually sufficient for a convergent and correct solution. In the context of this study, the sample size was guided by Kline [23] where the author suggested a tool to estimate an appropriate sample size [24]. The following parameters were adjusted in the tool: anticipated effect size: 0.3, desired statistical power level: 0.8, number of latent variables: 8, number of observed variables: 26, probability level: 0.05. As a result, the recommended minimum sample size was 177. Since the actual sample size of this research was 395, exceeding the above-mentioned thresholds

TABLE I
CONSTRUCTS, ITEMS, AND SOURCE OF MEASUREMENT MODEL

Code	Items
PE	**Performance Expectancy [1]**
	(PE1) I would find Google Lens useful for my teaching and learning.
	(PE2) I think using Google Lens will enhance productivity in my job.
	(PE3) I think using Google Lens will help me save searching time.
EE	**Effort Expectancy [1]**
	(EE1) I would find Google Lens easy to use.
	(EE2) I would not take me long to learn how to use Google Lens.
	(EE3) My interaction with Google Lens would be clear and understandable
	(EE4) It would be easy for me to become skillful at using Google Lens.
SI	**Social Influence [1]**
	(SI1) People who influence my behavior think that I should use Google Lens for my daily jobs.
	(SI2) I think I am more likely to use Google Lens if my friends and my family use it.
	(SI3) I use Google Lens because of my colleagues who use the application.
FC	**Facilitating Conditions [1]**
	(FC1) I have the resources necessary to use Google Lens.
	(FC2) I have the knowledge necessary to use Google Lens.
	(FC3) Google Lens is compatible with my devices.
	(FC4) If I have problem using Google Lens, I can get help from the service provider.
HM	**Hedonic Motivation [5]**
	(HM1) I think using Google Lens is fun.
	(HM2) I think using Google Lens is entertaining.
	(HM3) I think using Google Lens is enjoyable.
UV	**Utilitarian Value [6]**
	(UV1) I find it easy to get the Google Lens features to do what I want to do.
	(UV2) The provided features on Google Lens helped me better finding information.
	(UV3) Using the features on Google Lens enables me to accelerate teaching/learning.
PR	**Perceived Risk [8]**
	(PR1) I think using Google Lens puts my privacy at risk.
	(PR2) Using Google Lens exposes me to an overall risk.
	(PR3) Using Google Lens will not fit well with my self-image.
BI	**Behavioral Intention [1]**
	(BI1) I intend to use Google Lens in the next six months for teaching/learning.
	(BI2) I predict I will use Google Lens in the next six months.
	(BI3) I plan to use Google Lens each time I need it for teaching/learning.

(177), it can be concluded that the required sample size for the present study was met.

C. Measures

After studying the questions used for the survey based on the research model, 26 questions were selected and included in the research (see Table I). A five-point Likert scale (1 = Disagree, 2 = Tend to disagree, 3 = Neutral, 4 = Tend to agree, 5 = Totally Agree) was used for each question.

D. Data Analysis

Generalized structured component analysis (GSCA), because of its flexibility to work with a limited sample size but without requiring rigorous normal distribution, was employed to evaluate this proposed study model [25]. GSCA is a structural equation model-based component and is suitable for the modeling of Partial Least Squares (PLS) paths. This technique, proposed by Hwang and Takane [25], enables an algorithm (i.e., Alternating Least Square algorithm (ALS)) to optimize a global function. GSCA is a tradition of the analysis of components. It replaces components with PLS-like factors. However, in contrast to PLS, GSCA provides a global criterion of the least square parameters, which is consistently minimized to calculate model parameters. Therefore, GSCA has an overall measure of model fit and maintains all the advantages of PLS. Moreover, compared to PLS, the GSCA processes more diverse path analyses. Web-based GSCA [26] software was used for parameters estimation.

IV. RESULTS

A. Demographic characteristics

Table II displayed descriptive data on the demographic information of participants. 25.32% of the participants were male, and 60.25% were female, 14.43% of the respondents did not prefer to identify their gender. Nearly all participants had master's degrees (82.03%), followed by having bachelor's degree (13.67%), and vocational training (4.30%). More than half of the subjects are living in cities (61.52%), the rest lived in towns (22.53%), and rural area (15.95%). In terms of age distribution, nearly half of the participants were from 31 to 40 years of age, followed by 32.41% for a range of 21 to 30, only a small portion of users is either young (6.84%) or mature (3.79%).

TABLE II
GENERAL INFORMATION ABOUT THE PARTICIPANTS

Variable	Category	Number	Percentage
Gender	Male	145	25.32
	Female	238	60.25
	Not to say	12	14.43
Age	10 to 20	27	6.84
	21 to 30	128	32.41
	31 to 40	192	48.61
	41 to 50	33	8.35
	Over 51	15	3.79
Area of living	City	243	61.52
	Town	89	22.53
	Rural Area	63	15.95
Level of Education	Undergraduate	54	13.67
	Graduate	324	82.03
	Vocational Training	17	4.30
Total		**395**	**100**

B. Quantitative analysis

Table III displayed the descriptive statistics for the construct items. The table showed that all of the means of the extended UTAUT measures were greater than the average point of 3, with standard deviations ranging from 0.738 to 1.398.

TABLE III
MEANS AND STANDARD DEVIATIONS OF THE MEASURES (N=395)

Construct	**Item**	**Mean**	**SD**
Performance Expectancy	PE1	4.281	0.948
	PE2	4.203	0.942
	PE3	4.041	1.096
Effort Expectancy	EE1	4.349	0.890
	EE2	4.352	0.819
	EE3	4.316	0.895
	EE4	4.233	0.957
Social Influence	SI1	4.329	0.941
	SI2	4.251	0.926
	SI3	4.134	0.979
Facilitating Conditions	FC1	4.514	0.738
	FC2	4.425	0.826
	FC3	3.623	1.234
	FC4	3.570	1.105
Hedonic Motivation	HM1	4.081	1.022
	HM2	4.053	0.852
	HM3	3.987	0.914
Utilitarian Value	UV1	3.803	0.985
	UV2	3.932	0.897
	UV3	3.876	0.975
Perceived Risk	PR1	3.172	1.398
	PR2	3.134	1.391
	PR3	3.823	1.030
Behavioral Intention	BI1	4.213	0.935
	BI2	4.220	0.969
	BI3	4.296	0.896

Table IV showed the internal consistency and convergent validity metrics for each construct. Dillon–Goldstein's rho was used to assess each construct's internal consistency reliability criteria. Almost of the results, ranging from 0.8147 to 0.8879, were larger than 0.7, exceeding the acceptable reliability estimate in [25], except the construct "Facilitating Conditions" which had a score of 0.6766 (lower than the recommended score). We also looked at the average variance extracted (AVE) value of each latent variable to see if it was convergent. All AVE values (also except the construct FC) were larger than 0.5, ranging from 0.6259 to 0.7134, indicating a reasonable convergent validity. Thus, the construct "Facilitating Conditions" was removed in the generalized structured component analysis.

TABLE IV
INTERNAL CONSISTENCY AND CONVERGENT VALIDITY

Construct	Item	Rho	AVE
Performance Expectancy	3	0.8543	0.6617
Effort Expectancy	4	0.8879	0.6653
Social Influence	3	0.8356	0.6302
Facilitating Conditions	4	0.6766	0.4316
Hedonic Motivation	3	0.8517	0.6582
Utilitarian Value	3	0.8815	0.7134
Perceived Risk	3	0.8147	0.6259
Behavioral Intention	3	0.8720	0.6965

Table V showed the loading estimates for the items (after the construct FC along with its items were removed), as well as their standard errors (SEs) and 95 percent bootstrap percentile confidence intervals (CIs) with lower and upper limits (LB, and UB respectively). The confidence intervals (CIs) were generated using 100 bootstrap samples. If the 95 percent CI did not include the value zero, a parameter estimate was assumed to be statistically significant at the 0.05 alpha level. All the loading estimates were statistically significant, suggesting that all those items were reliable indicators of the constructs.

TABLE V
ESTIMATE OF LOADINGS

	Estimate	Std Error	95% CI_LB	95% CI_UB
PE1	0.7802	0.0325	0.7168	0.8417
PE2	0.8406	0.0222	0.7984	0.8799
PE3	0.8182	0.0236	0.7712	0.8615
EE1	0.7259	0.0375	0.6359	0.8048
EE2	0.842	0.0230	0.7935	0.8879
EE3	0.8566	0.0201	0.8189	0.8927
EE4	0.8315	0.0194	0.7918	0.8632
SI1	0.7453	0.0364	0.6625	0.8179
SI2	0.8722	0.0183	0.8333	0.9093
SI3	0.7580	0.0350	0.6775	0.806
HM1	0.7392	0.0296	0.6813	0.7985
HM2	0.8936	0.0097	0.8752	0.9107
HM3	0.7936	0.0284	0.7352	0.8491
UV1	0.8956	0.0114	0.8732	0.9216
UV2	0.8608	0.0181	0.8156	0.8917
UV3	0.7727	0.0280	0.7191	0.8197
PR1	0.9301	0.0120	0.9053	0.9489
PR2	0.9443	0.0080	0.9267	0.9581
PR3	0.3477	0.0882	0.1290	0.5035
BI1	0.8626	0.0211	0.8122	0.8925
BI2	0.9252	0.0088	0.9087	0.9402
BI3	0.6997	0.0414	0.6206	0.7744

Table VI showed that GSCA provided FIT = 0.5187 (SE = 0.0096, 95% CI = 0.5035 – 0.5393), AFIT = 0.5159 (SE = 0.0097, 95% CI = 0.5006 – 0.5366), GFI = 0.9852 (SE = 0.0012, 95% CI = 0.9829 – 0.9876), and SRMR = 0.1875 (SE = 0.0091, 95% CI = 0.1755–0.2148). Both FIT and Adjusted FIT (AFIT) considered the variance of the data explained by a given model specification. FIT values vary from 0 to 1. In linear regression, the properties, and interpretations of FIT and AFIT are equivalent to R^2 and Adjusted R^2. According to FIT and AFIT, the model accounted for approximately 51.87 percent and 51.59 percent of the total variance of all variables, respectively. The statistical difference between FIT and AFIT was substantially different from zero. Next, goodness-of-fit index (GFI) and standardized root mean square residual (SRMR) represent the proximity between sample covariance and covariance, as another measurement of the overall model fit. The numbers GFI around 1 and SRMR near 0 might be considered as a sign of good fit. The GFI value was extremely near to 1, whereas the SRMR value was rather large and statistically different from zero.

TABLE VI
MODEL FIT

	Measure	Std. Error	95% CI_LB	95% CI_UB
FIT	0.5187	0.0096	0.5035	0.5393
Adjusted FIT (AFIT)	0.5159	0.0097	0.5006	0.5366
GFI	0.9852	0.0012	0.9829	0.9876
Standardized Root Mean Square (SRMR)	0.1875	0.0091	0.1755	0.2148

Table VII provided the estimates of path coefficients in the structural model along with their SEs and 95% CIs. In general, the interpretations of the path coefficient estimates are compatible with the connections between the components postulated in the model. That is, performance expectancy had statistically significant and positive impact on behavioral intention (H1 = 0.2752, SE = 0.078, 95% CI = 0.1096 – 0.4112). In turn, utilitarian value had a statistically significant and positive influence on behavioral intention (H6 = 0. 2026, SE = 0.0465, 95% CI = 0.0963–0.2809). Social influence also had statistically significant and positive impact on behavioral intention (H3 = 0.3705, SE = 0.0769, 95% CI = 0.2472 – 0.5418). Moreover, perceived risk had statistically significant

TABLE VII
ESTIMATES OF PATH COEFFICIENTS

	Estimates	Std. Error	95% CI_LB	95% CI_UB
EE → BI	0.0256	0.0609	-0.0981	0.1213
PE → BI	0.2752*	0.078	0.1096	0.4112
HM → BI	-0.0408	0.0428	-0.1206	0.0586
UV → BI	0.2026*	0.0465	0.0963	0.2809
SI → BI	0.3705*	0.0769	0.2472	0.5418
PR → BI	-0.1126*	0.0392	-0.1906	-0.0381

* statistically significant at 0.05 level.

and negative effect on behavioral intention (H7 = -0.1126, SE = 0.0392, 95% CI = -0.1906 – -0.0381). However, hypotheses H2 (Effort Expectancy → Behavioral Intention) and H5 (Hedonic Motivation → Behavioral Intention) were not supported due to the presence of zero values in CIs. The hypothesis H1 (Facilitating Conditions → Behavioral Intention) was not considered in this analysis due to the dissatisfaction of validity and consistency.

C. Discussions

With the advent of information and communication technology, teaching and learning through augmented reality applications has taken on an unprecedented significance in educational settings. AR apps for teaching and learning bridge the gap between the actual world and the virtual environment to give learners with a better experience and value [27-30]. Recognizing previous research that studied AR applications, AR academics have mostly concentrated on the technological aspects and acceptance (e. g. perceive of use, usefulness, visual design, task technology fit, etc.) of AR apps [28, 29, 31, 32]. There have been few attempts to investigate the possibility of utilizing Google Lens in education domain [9-11], however, Google Lens's potential is currently limited. As a result, the current study boosted awareness among both consumers and AR app developers.

The present study makes a twofold contribution. In the first place, we extended the Unified Theory of Acceptance and Use of Technology (UTAUT) theoretical model demonstrating the factors affecting the behavioral intention to use Google Lens. To the best of the authors' knowledge, this is one of the first studies to uncover a set of effects from AR features to user behaviors taking into account of AI and AR. As such, the findings of this study contribute new insights to the AR education and user behavior literatures by highlighting the implications of Google Lens app use in teaching/learning at home environments. Second, the study integrated perceived risk as one of the developing constructs in AR research. Traditionally, the AR system relied solely on picture collection from a camera, analysis of an area of interest, and superimposition of media contents [28, 33]. More information was gathered over time (e.g., location, device orientation, user history) in order to deliver a better user experience [30, 34]. As a result, user privacy may be compromised. The results of this study showed that users did not likely utilize Google Lens when they felt their privacy had been broken, implying that developers should pay attention to this issue.

Despite the contributions described above, several limitations confine the findings inevitably. Together with the unanticipated outcomes, these limitations lead to a promising platform for study into the future. First, non-probability sampling was used in this study to guarantee that the respondents are those who have children in their families but must keep them at home owing to social distance. However, as generally acknowledged in the literature, this sampling strategy limits the generalizability of the findings beyond the sample characteristics provided in this study. Second, this study investigated the use of Google Lens in a short period of time. In view of the speed of technological progress, the results of this study must be reviewed as technologies move forward. Third, because the current study used just three external variables as the theoretical framework, other factors not included in the UTAUT could not be assessed.

V. Conclusions

This study analyzed the impacts of factors affecting the intention to use Google Lens. The extended Unified Theory of Acceptance and Use of Technology model was adapted to measure user behavior toward experiencing the Google Lens AR application in terms of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, utilitarian value, and perceived risk. Using data of 395 participants, the study results showed that performance expectancy had statistically significant and positive impact on behavioral intention, utilitarian value had a statistically significant and positive influence on behavioral intention, social influence also had statistically significant and positive impact on behavioral intention, perceived risk had statistically significant and negative effect on behavioral intention. However, this study did not find significant relationships between the effort expectancy and the behavioral intention, nor between the hedonic motivation and the intention to use the Google Lens application. Due to the dissatisfaction of validity and consistency, the factor "Facilitating Conditions" was not included in the analysis. The reasons for these non-significant correlations will be examined further in a large-scale user experience research.

References

[1] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS quarterly*, vol. 27, no. 3, pp. 425-478, 2003.

[2] K. Fuchs, "How are small businesses adapting to the new normal? Examining tourism development amid COVID-19 in Phuket," *Current Issues in Tourism*, pp. 1-5, 2021.

[3] J. A. Pacheco, "The "new normal" in education," *Prospects*, pp. 1-12, 2020.

[4] G. LLC. "Search what you see." https://lens.google/ (accessed 6/4, 2018).

[5] R. M. Ryan and E. L. Deci, "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being," *American psychologist*, vol. 55, no. 1, p. 68, 2000.

[6] B. J. Babin, W. R. Darden, and M. Griffin, "Work and/or fun: measuring hedonic and utilitarian shopping value," *Journal of consumer research*, vol. 20, no. 4, pp. 644-656, 1994.

[7] A. Chennapragada. "Helpful new visual features in Search and Lens." https://www.blog.google/products/search/helpful-new-visual-features-search-lens-io/ (accessed 5/7, 2019).

[8] M. S. Featherman and P. A. Pavlou, "Predicting e-services adoption: a perceived risk facets perspective," *International journal of human-computer studies*, vol. 59, no. 4, pp. 451-474, 2003.

[9] A. N. Devi and G. Gaurav, "Reviews on Augmented Reality: Google Lens," *International Journal of Computer Trends and Technology*, vol. 58, no. 2, pp. 94-97, 2018.

[10] Y. B. Shapovalov, Z. I. Bilyk, A. I. Atamas, V. B. Shapovalov, and A. D. Uchitel, "The Potential of Using Google Expeditions and Google Lens Tools under STEM-education in Ukraine," *arXiv preprint arXiv:1808.06465*, 2018.

[11] V. Shapovalov, Y. Shapovalov, Z. Bilyk, A. Megalinska, and I. Muzyka, "The Google Lens analyzing quality: an analysis of the possibility to use in the educational process," 2019.

[12] Z. I. Bilyk, Y. B. Shapovalov, V. Shapovalov, A. Megalinska, and A. Dołhańczuk-Śródka, "Assessment of mobile phone applications feasibility on plant recognition: comparison with Google Lens AR-app," in *Proceedings of the 3rd International Workshop on Augmented Reality in Education (AREdu 2020), Kryvyi Rih, Ukraine*, 2020.

[13] B. Lucia, M. A. Vetter, and O. Moroz, "The Rhetoric of Google Lens: A Postsymbolic Look at Locative Media," *Rhetoric Review,* vol. 40, no. 1, pp. 75-89, 2021.

[14] D. Viswanadhuni, M. L. Dalmet, M. Raghavendra Kalose, S. Mukherjee, and K. Ravi Kiran, "Domain Knowledge Embedding Based Multimodal Intent Analysis in Artificial Intelligence Camera," in *Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4-6, 2020, Revised Selected Papers, Part II 5*, 2021: Springer Singapore, pp. 281-292.

[15] N. A. Sergeeva, A. N. Zakharova, O. S. Rublyova, and S. I. Tyutyunnik, "Features of using methods and means of the augmented reality technology when teaching a foreign language," *Перспективы науки и образования,* no. 2, pp. 472-486, 2021.

[16] J. Rebekah, D. J. W. Wise, D. Bhavani, P. A. Regina, and N. Muthukumaran, "Dress code Surveillance Using Deep learning," in *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2020: IEEE, pp. 394-397.

[17] A. Kumar, K. Srinivasan, W.-H. Cheng, and A. Y. Zomaya, "Hybrid context enriched deep learning model for fine-grained sentiment analysis in textual and visual semiotic modality social data," *Information Processing & Management,* vol. 57, no. 1, p. 102141, 2020.

[18] F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems," *Cambridge, MA,* 1986.

[19] J.-H. Wu and S.-C. Wang, "What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model," *Information & management,* vol. 42, no. 5, pp. 719-729, 2005.

[20] M. Fishbein and I. Ajzen, "Belief, attitude, intention, and behavior: An introduction to theory and research," 1977.

[21] N. Kock and P. Hadaya, "Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods," *Information Systems Journal,* vol. 28, no. 1, pp. 227-261, 2018.

[22] J. C. Anderson and D. W. Gerbing, "The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis," *Psychometrika,* vol. 49, no. 2, pp. 155-173, 1984.

[23] R. B. Kline, *Principles and practice of structural equation modeling*. Guilford publications, 2015.

[24] D. Soper. "Calculator: a-priori sample size for structural equation models." https://www.danielsoper.com/statcalc/calculator.aspx?id=89 (accessed 10/10, 2006).

[25] H. Hwang and Y. Takane, *Generalized structured component analysis: A component-based approach to structural equation modeling*. CRC Press, 2014.

[26] H. Hwang, G. Cho, and H. Choo. "Generalized Structured Component Analysis." http://sem-gesca.com/webgesca/ (accessed.

[27] R. Azuma, Y. Baillot, R. Behringer, S. Feiner, S. Julier, and B. MacIntyre, "Recent advances in augmented reality," *IEEE computer graphics and applications,* vol. 21, no. 6, pp. 34-47, 2001.

[28] V. T. Nguyen, K. Jung, S. Yoo, S. Kim, S. Park, and M. Currie, "Civil War battlefield experience: Historical event simulation using augmented reality technology," in *2019 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, 2019: IEEE, pp. 294-2943.

[29] K. Jung, V. T. Nguyen, S.-C. Yoo, S. Kim, S. Park, and M. Currie, "PalmitoAR: The Last Battle of the US Civil War Reenacted Using Augmented Reality," *ISPRS International Journal of Geo-Information,* vol. 9, no. 2, p. 75, 2020.

[30] V. T. Nguyen, K. Jung, and T. Dang, "BlocklyAR: A Visual Programming Interface for Creating Augmented Reality Experiences," *Electronics,* vol. 9, no. 8, p. 1205, 2020.

[31] V. Saprikis, G. Avlogiaris, and A. Katarachia, "Determinants of the Intention to Adopt Mobile Augmented Reality Apps in Shopping Malls among University Students," *Journal of Theoretical and Applied Electronic Commerce Research,* vol. 16, no. 3, pp. 491-512, 2021.

[32] R. VONGURAI, "Factors Influencing Experiential Value Toward Using Cosmetic AR Try-on Feature in Thailand," *Journal of Distribution Science,* vol. 19, no. 1, pp. 75-87, 2021.

[33] V. T. Nguyen, R. Hite, and T. Dang, "Learners' technological acceptance of vr content development: A sequential 3-part use case study of diverse post-secondary students," *International Journal of Semantic Computing,* vol. 13, no. 03, pp. 343-366, 2019.

[34] K. Jung, V. T. Nguyen, D. Piscarac, and S.-C. Yoo, "Meet the virtual jeju dol harubang—The mixed VR/Ar application for cultural immersion in Korea's main heritage," *ISPRS International Journal of Geo-Information,* vol. 9, no. 6, p. 367, 2020.