Video-Based Learning Adoption: A typology of learners

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Abstract. This work builds on complexity theory in order to identify different types of learners that use video-based learning (VBL). VBL has great value as an educational tool which has already been identified in various contexts. This study combines learners' demographics with learners' experience in a conceptual model to explain the adoption of VBL technologies. We test and validate the proposed model through a survey on 260 VBL users, by implementing the data analysis tool fsQCA (fuzzy-set Qualitative Comparative Analysis). The findings indicate eight configurations of learners' demographics and learners' experience that lead to high intention to adopt VBL. The results take a step further the literature of VBL by taking a different approach and implementing a different methodology, which has recently started to receive increasing attention. We also offer theoretical and practical implications by identifying distinct types of learners that have high behavioral intentions towards VBL.

Keywords: Video-Based Learning; VBL; e-learning; Experience; Fuzzy-set qualitative comparative analysis.

1. Introduction

The implementation of learning videos as educational tools is increasing rapidly the past years. Researchers focus on video-based learning (VBL), which is defined as *the learning process of acquiring defined knowledge, competence, and skills with the systematic assistance of video resources [1]*. The successful implementation of VBL in education is based on convincing learners to adopt such tools and use the available videos to gain knowledge. Recent studies in the area have focused on examining the role of various factors on learners' behavior towards using VBL (e.g., [2]). To this end, adoption theories (e.g., UTAUT, SCT, TPB) have been used to explain learners' behavior. Nonetheless, VBL adopters have different characteristics that affect their behavior, and depending on how they appear they might be able to predict adoption. For example, demographic factors and previous experience are some of the most common factors that influence behavior. However, no previous study has tried to produce a typology of learners that use VBL based on their demographics and experience.

The study examines the following contingent variables: gender, age, education, and previous experience with learning videos, (i.e., times watched learning videos and minutes spent watching a learning video). The study also considers learners' behavioral intention to adopt VBL. To this end, we propose a conceptual model and aim to explore the causal patterns of factors that stimulate learners to adopt VBL. The goal of this

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study is to detect specific configurations that explain VBL adoption, and create a typology of VBL learners. Thus, the study addresses the following research question:

What configurations of demographic characteristics and experience with VBL, predict high behavioral intentions to adopt VBL?

The identification of the aforementioned configurations may aid universities and colleges to better target their learners when they offer VBL for their courses. To answer the research question we employ complexity theory and configurational analysis using fuzzy set qualitative comparative analysis (fsQCA) [3, 4], which has received increased attention the past because it may offer the researchers a better perspective on the data [3, 5].

The paper has the following structure. Section 2 reviews the related literature and presents the conceptual model. Section 3 described the research methodology and the data used to evaluate the proposed model. Section 4 presents the empirical findings and section 5 concludes the study by discussing ideas for future work in the area of VBL.

2. Related Work and Conceptual Model

The adoption and acceptance of various e-learning tools has been examined with different adoption models and theories, such as UTAUT2, TPB, and SCT. Previous studies have identified several important factors as antecedents of intention to adopt e-learning technologies [6] and video-based learning [7]. Following this stream of research, a number of studies have engaged in empirical assessments of how various demographics influence behavioral intention to adopt e-learning technologies. Users' demographic characteristics and previous experience have been identified as very important factors in adoption theories and have been examined widely as moderators of the relationship between the various antecedents of adoption and behavioral intentions (e.g., UTAUT, UTAUT2). Demographic characteristics refer to learners' gender, age, and level of education. Wang et al. [8] find that age has a moderating impact on factors that influence behavioral intention. Other gender differences regarding adoption are noted by Liao et al. [9] whom although place their examination in a different context find that gender has a significant effect.

Further, previous experience refers to how many times a learner has used videos for learning the past six months and for how long the learner watched the video. Prior research on e-learning and VBL uses various symmetric tests (e.g., multiple regression analysis) to explain adoption and examines these factors as moderators or control variables. In learning adoption and continuance research models, split groups analyses also pinpoint that there are significant differences between groups of learners that are considered experienced compared to those without any prior experience [10]. The thesis for different behaviors depending on experience is that perceptions evolve through the discourse of engaging with a technology and gaining familiarity with similar means [11]. Sun et al. [12], find that anxiety of using an e-learning medium can be a detrimental factor, thus, with frequent use of a specific medium anxiety is lessened and adoption and satisfaction levels are enhanced.

Despite the aforementioned studies and their findings, demographics and experience are very seldom examined simultaneously; therefore, there is limited understanding on how factors that appertain to learner demographics and experience coalesce to shape behavioral intentions to use VBL applications. Given the fact that there are multiple types of learners engaging with VBL, the purpose of this research is to extract a typology of learners using VBL. Thus, we suggest an alternative approach to tackle this question. The methodological approach used in this study builds on identifying the various combinations among the variables of interest. In other words, these combinations will describe which learners' characteristics increase intention to adopt VBL and offer different categories of learners. The main differentiating aspect of this approach is that multiple different types of learners can be discovered.

The proposed model is illustrated with a Venn diagram (Figure 1) and presents three sets of constructs and their intersections. The three sets reflect (i) the outcome of interest (i.e., dependent variable) and (ii) two sets of causal conditions to act as predictors (i.e., independent variable). The outcome of interest is learners' behavioral intention to adopt VBL, and demographic characteristics (i.e., gender, age, education) and experience (i.e., times watched a video, minutes watched a video). The intersections among the three sets of constructs represent factors, which are higher level interactions.

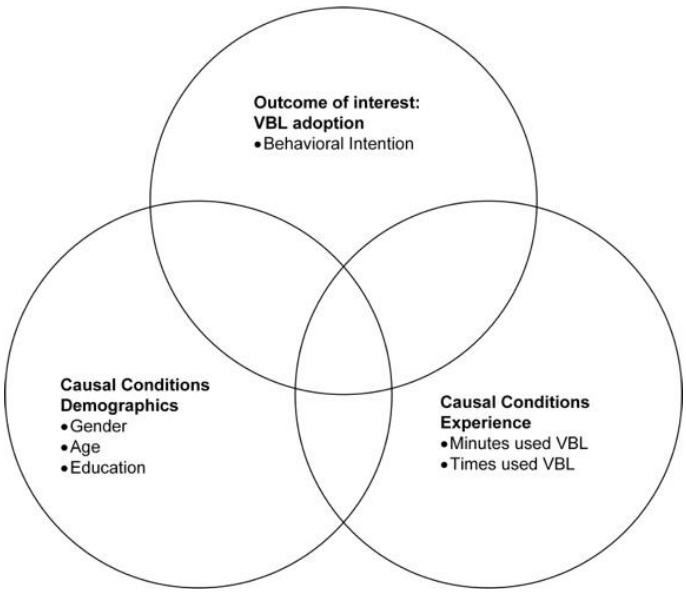

Fig. 1. Venn diagram of the conceptual model

3. Research Methodology

3.1. Data Collection

A questionnaire on video based learning yielded the data for this study. The participants responded either in person or online. Questionnaires were distributed for two months in various locations (universities, public areas) and e-mails with digital questionnaires sent to a number of mailing lists of individuals with experience in educational activities through VBL. We targeted about 1000 learners, and 302 responded, out of which only 260 had used VBL the past six months, thus comprising our sample. The sample consists of almost equally men (49.6%) and women (50.4%). Regarding age, the majority (36.2%) were between 21 and 25 years old, followed by people between 26-30 years old (24.4%). The rest were older than 30 years (23.1%), and 20 years old or younger (16.3%). Regarding education, the sample consists almost equally of university graduates (46.3%) and postgraduates (44.7%), while a small percentage (8.9%) were high school graduates.

3.2. fsQCA Methodology

The study applies fuzzy-set Qualitative Comparative Analysis (fsQCA) using fs/QCA 2.0 [3, 4]. fsQCA identifies patterns of elements, between independent and dependent variables, that lead to an outcome and goes a step further from the analyses of variance, correlations and multiple regression models. Further, fsQCA offers two types of configurations that include necessary and sufficient conditions. Such configurations may be marked by their presence, their absence, or a "do not care" condition. The necessary and the sufficient conditions create a distinction among core and peripheral elements. Core elements are those with a strong causal condition with the outcome, peripheral elements are the ones with a weaker one [13]. For variables with binary values (0/1) (e.g., gender), crisp-set qualitative comparative analysis is suitable (csQCA). fsQCA differs as it is suitable for both discrete and continuous variables.

3.3. Raw data calibration

fsQCA requires the definition of the outcome and the independent measures. Next, all measures need to be calibrated into fuzzy sets with values ranging from 0 to 1. In detail, the value of 1 stands for the full set membership, while that of 0 stands for the no set membership. Table 1 describes the calibration of the raw data.

Regarding the continuous variable measured with a 7 point Likert scale (i.e., Behavioral intention) the scale from 0-1, defines the level of their membership. The transformation of variables into calibrated sets is done by fsQCA program, by setting three meaningful thresholds; full membership, full non-membership, and the cross-over point, which describes how much the case belongs to a set [4]. The calibration is done by following the procedure employed by Ordanini et al. [14]. With this calibration method, the three qualitative anchors for the calibration, are based on the survey scale

(7-point Likert). The full membership threshold is fixed at the 6; the full non-membership threshold is fixed at 2; and, the crossover point was fixed at 4.

The calibration of the discrete variables here is simpler since they only take two values, 1 for the full set membership and 0 for the no set membership. Contrary to the continuous variable, the technique used for the discrete variables is direct calibration. Gender is a binary variable. Regarding education, postgraduates were defined as the full set membership and the rest as the full non-membership. Next, the median of age and experience was computed, thus creating the categories of young and older, and high and low experience in terms of times used VBL and minutes watched a video.

Table 1. Calibration of the raw data

Conditions/outcome	**fuzzy-set QCA (fsQCA)**
Gender	Male → 1 Female → 0
Age	Under 25 → 1 25 or older → 0
Education	Post Graduate → 1 High School or University → 0
Experience	10 times or more → 1 Less than 10 times → 0
	10 minutes or more → 1 Less than 10 minutes → 0
Behavioral Intention	6 → Full membership 4 → Crossover point 2 → Full non-membership

After the calibration, the fsQCA algorithm is applied in order to create a truth table of 2^k rows, where *k* represents the number of outcome predictors, and each row represents every possible combination. Next, the truth table needs to be sorted out based on frequency and consistency [4]. The frequency describes the number of observations for every combination (i.e., row). Consistency refers to *"the degree to which cases correspond to the set-theoretic relationships expressed in a solution" [13]*. Following, we set a cut-off point regarding frequency, which will set the minimum number of empirical observations. Following the recommendations of Ragin [4] and Fiss [13], for large-scale samples (e.g., 150 and more cases) the minimum acceptable observation frequency is set at three, and the lowest acceptable consistency for observations is set at >.90, significantly higher than the recommended threshold of 0.75 [4].

4. Findings

The outcomes of the fuzzy set analysis for high behavioral intentions to use VBL are presented in Table 2. In detail, black circles (●) indicate the presence of a condition, while crossed-out circles (⊗) indicate its absence [2]. Blank spaces suggest a do not care situation, in which the causal condition may be either present or absent. The solution table includes values of set-theoretic consistency for each configuration as well as for the overall solution, with all values being above threshold (>0.75). Consistency measures the degree to which a subset relation has been approximated, whereas coverage assesses the empirical relevance of a consistent subset [4]. The overall solution coverage indicates to what extent high behavioral intentions may be determined based on the set of configurations, and is comparable to the R-square value reported in correlational methods [5]. The results offer an overall solution coverage of .50, which suggests that a substantial proportion of the outcome is covered by the eight solutions.

Table 2. Configurations for achieving high level behavioral intentions to use VBL

	Solution							
Configuration	1	2	3	4	5	6	7	8
Demographics								
Gender *(Male)*		⊗	●	●		⊗	●	●
Age *(<25)*	●		●	⊗	⊗	●	●	⊗
Education *(PostGraduates)*	⊗	⊗		●	●		●	⊗
Experience/use								
Over 10 Times used	●		●	●	●	●		
Over 10 Minutes watched	●	●	●		●	⊗	●	⊗
Consistency	.94	.92	.95	.95	.96	.92	.94	.98
Raw Coverage	.17	.16	.13	.06	.06	.06	.04	.04
Unique Coverage	.11	.11	.09	.04	.04	.06	.02	.04
Overall solution consistency	0.98							
Overall solution coverage	0.50							
Note: Black circles (●) indicate the presence of a condition, and circles with “x” (⊗) indicate its absence. Both circles indicate core conditions. Blank spaces indicate “don’t care”.								

The times a learner used VBL and the minutes he or she watched the learning videos are key conditions in predicting behavioral intentions to adopt VBL, because they are present in five out of eight configurations. As presented in table 3, fsQCA evaluates the causal configurations with the greatest raw coverage [4]. The configurations with high coverage values imply that they have the greatest empirical relevance. Solutions 1-3 present such configurations.

In detail, for solution 1 the raw coverage is 0.17, which suggests that 17% of the young users of learning videos who are high school or university graduates, have high experience with learning videos, and watch the videos for over 10 minutes have high intentions to adopt VBL. The raw coverage for solution 2 is 0.16, which suggests that 16% of women who are high school or university graduates, and watch learning videos for over 10 minutes have high intentions to adopt VBL. Finally, solution 3 with raw coverage 0.13, suggests that 13% of young males, who have high experience with learning videos, and watch the videos for over 10 minutes, have high intentions to adopt VBL. The following table (Table 3) describes the findings for each solution.

Table 3. Learner typologies for high behavioral adoption to use VBL

1. Young graduates that have watched learning videos more than ten times and for over ten minutes
2. Female graduates that watch learning videos for more than minutes.
3. Young males that have watched learning videos more than ten times and for over ten minutes
4. Old postgraduate males that have watched learning videos more than ten times.
5. Old postgraduates that have watched learning videos more than ten times and for over ten minutes
6. Young females that have watched learning videos more than ten times and for less than ten minutes.
7. Young postgraduate males that watch learning videos for over ten minutes
8. Old male graduates that watch learning videos for less that ten minutes

5. Discussion and conclusion

This study examines the behavioral intention of users to adopt video based learning. The study analyzes how users' demographic characteristics, such as gender, age, education, combine with experience with learning videos in order to predict intention to adopt VBL. To this end, a conceptual model is proposed in order to explain the aforementioned relationships. The findings describe the different types of users that may have high behavioral intentions to adopt VBL. This research contributes to the video based learning literature. This study adopts a novel analysis methodology (i.e., fsQCA) and offers complex but parsimonious patterns, on which the antecedents may be present or absent, suggesting how the various characteristics combine to explain users' behavior.

Previous studies explain users' behavioral intentions by focusing on the main effects of various antecedents on one or more dependent variables. However, the different factors may coexist and various combinations may lead to the same outcome. For example, being highly educated (i.e., postgraduate) does not always suggest high behavioral intentions, depending on gender, age, and experience. This research makes a step towards creating new theories in VBL, as it performs configurational analysis based on individual-level data from users of learning videos, which has been proven appropriate for theory building [5].

Future research should examine other variables as well, which have been proven to influence the behavior of VBL users. Such factors, combined with demographics and experience may be able to better predict behavior and while suggesting where researchers and practitioners should focus. In addition, future studies may examine a different outcome of interest, such as the actual use of learning videos. Finally, future research should apply and evaluate the proposed model and method on specific e-learning tools (e.g., flipped classroom, MOOCs).

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