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# User Engagement with Interactive Educational Videos: Relations with Task Value, Cognitive Load, and Learning Satisfaction

**Xiao-Feng Kenan Kok**
Singapore Institute of Technology, Singapore, *kenan.kok@singaporetech.edu.sg*

**Peng Cheng Wang**
Singapore Institute of Technology, Singapore, *victor.wang@singaporetech.edu.sg*

**Karin Avnit**
Singapore Institute of Technology, Singapore, *karin.avnit@singaporetech.edu.sg*

**Monika Shukla**
Singapore Institute of Technology, Singapore, *monika.shukla@singaporetech.edu.sg*

Interactive educational videos have grown in popularity in the higher education setting over the last two decades. This exploratory study investigates the mediating and moderating effects of user engagement (UE) on the relationships between the antecedents of UE (i.e., intrinsic load, extraneous load, germane load, and task value) and learning satisfaction. A cross-sectional survey study was conducted in June 2023. We conveniently sampled 49 year-one undergraduate students, who completed a self-report questionnaire consisting of items pertaining to cognitive load, task value, user engagement, and learning satisfaction. Data was analysed using hierarchical linear regression models. Findings revealed that reward fully mediated the relationship between germane load and learning satisfaction. In addition, reward was also found to moderate the relation between (a) germane load and learning satisfaction, and (b) task value and learning satisfaction. These findings highlight the importance of creating rewarding experiences when designing interactive educational videos.

Keywords: user engagement, interactive educational videos, task value, cognitive load, learning satisfaction

## INTRODUCTION

In recent decades, researchers have extensively examined user engagement across various domains, such as digital health, marketing, social media, online communities, online search, and learning, spanning across multiple types of devices, including personal computers, smartphone applications, wearables, public displays, and exhibitions (O’Brien & Cairns, 2016; O’Brien et al., 2022). Consensus exists within the literature that user engagement comprises affective, behavioural, and cognitive elements, as acknowledged by various researchers (e.g., O’Brien, 2016; Oh & Sundar,

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2015; Suh & Cheung, 2019). In other words, engaged students exhibit interest and a strong sense of belonging (affective), demonstrate active participation, and do not show disruptive behavioural tendencies (behavioural), and actively pursue challenges, invest effort, and exceed expectations by going the extra mile (cognitive) (O’Brien et al., 2022). While it is recognised that user engagement is multifaceted, recent research has raised concerns about its applicability in diverse technological contexts (O’Brien et al., 2018). In a comprehensive review by Suh and Cheung (2019), a substantial portion of research on user engagement in technological contexts have focused primarily on areas such as social media, virtual worlds, mobile apps, online communities, shopping websites, image interactivity technologies, and patient order entry systems. However, it appears that there is a notable scarcity of research addressing user engagement within the technological domain of educational videos.

Educational videos have grown in popularity (Ploetzner, 2022; Preradović et al., 2020), infiltrating into our educational institutions, reshaping the methods of teaching, learning, studying, communicating, and working (Kaltura, 2015), and are broadly accepted as an effective instructional and learning resource in online, flipped, and blended learning courses (Borup et al., 2015; Chen, 2012). Such videos have been shown to improve student engagement (e.g., Mayer 2009; Ploetzner, 2022; Zhang et al., 2006), learning satisfaction (e.g., Hsin & Cigas, 2013; Wells et al., 2012; Zhang et al., 2006), and enhance interest in the subject domain (e.g., June et al., 2014). In recent times, a lot of research examining the impact of fine grain characteristics of educational videos (e.g., video length) and social endorsement cues (e.g., number of likes and dislikes, comments) on various learning outcomes (e.g., user engagement indicators, user satisfaction) have exploded onto the scene (e.g., Li et al., 2023; Qu et al., 2022; Yang et al., 2022). While previous studies have explored the benefits of educational videos and the impact of specific attributes or elements in these videos on learning outcomes, there is a noticeable gap in research that comprehensively examines cognitive load, user engagement, learning satisfaction, and task value of educational videos (cf. Altinpulluk et al., 2020).

In our study, we collectively investigated the above-mentioned constructs by developing a hypothesized conceptual model that builds on Suh and Cheung’s (2019) framework for user engagement (herein known as UEF or user engagement framework).We extended the UEF by adding cognitive load as an antecedent to our model as prior studies have demonstrated that the amount of cognitive load influences the extent of user engagement (Altinpulluk et al., 2020; Vesga et al., 2021). We selected task value as an antecedent and learning satisfaction as an outcome based on empirical evidence that indicates links amongst task value, user engagement, and learning satisfaction (see LITERATURE REVIEW for more details). By collectively examining cognitive load, task value, user engagement, and learning satisfaction, we aim to provide a more nuanced understanding of the factors influencing user engagement and how user engagement affects learning satisfaction. In this study, we developed our interactive educational videos based on Mayer’s design principles for multimedia learning, which is rooted in educational psychology, educational design, and the learning sciences (Mayer, 2009). By doing so, our research bridges a critical gap in the existing literature, where a lack of studies is evident that draw from educational or psychological theories as their foundation for the design of interactive educational videos.

**Literature Review**

**Interactive Educational Videos**

Educational videos have been characterized as influential technologies that hold a dominant position in contemporary e-learning environments (Bruce & Chiu, 2015). They are dynamic multimedia productions that often blend visual elements with spoken narrations (Ploetzner, 2022). As demonstrated by Ploetzner and Lowe (2012), the visual aspects may vary in terms of realism, spatial intricacy, and temporary dynamics. Similarly, the spoken narrations can exhibit variations in conversational style, intonation, and pacing, as observed by Fiorella and Mayer (2022). Various styles for educational videos exist, including lecture videos, voice-over slide shows, screen cast tutorials, and whiteboard explainer videos (for comprehensive overview, see Castillo et al., 2021; Köster, 2018). The ability of educational videos to disrupt the monotony of conventional learning materials, foster engagement, and maintain attention throughout the learning process has led researchers to delineate them as valuable literacy tools (Beach et al., 2010), a novel learning resource (Kalantzis & Cope, 2008), and potentially one of the most convenient tools in learning environments (Miller & Borowicz, 2005).

According to a meta-analysis by Ploetzner (2022), two main types of interaction features exist in educational videos. First, navigational interaction features encompass general controls, such as play and pause buttons, enabling learners to navigate within the educational content or access supplementary materials. Second, enhanced interaction features comprise domain-specific questions and tasks tailored to the subject matter, intended to facilitate better retention and comprehension. Owing to these interaction features that have been built into our educational videos, we shall refer to them as “interactive educational videos” rather than simply “educational videos”. As highlighted by Chen (2012), interactive videos integrate the dynamism of moving images, narrative elements of video, depth and richness of information, all while being enhanced with interactivity. This interactivity involves a format that encourages users to physically engage with the platform to enhance their learning experience (e.g., completing an embedded quiz in an educational video) (Aladé et al., 2016). Nonetheless, the exploration of enhanced interaction features within educational videos is relatively nascent, and hence there is a pressing need for more comprehensive and extensive research in this area (Ploetzner, 2022).

One of the key enhanced interaction features is that of quiz questions. In particular, immediate feedback on students’ responses to quiz questions provide an additional advantage (Rice et al., 2019). According to Johnson and Priest (2014), immediate feedback that is explanatory is notably more effective than simple corrective feedback (e.g., correct, or incorrect). By incorporating explanations along with the feedback, students’ perceptions of the videos featuring quiz questions could be potentially enhanced (Rice et al., 2019). Even though video embedded quiz questions did not appear to improve academic performance, the integration of such questions within videos enhanced interactivity and promoted greater engagement in the STEM (Science, Technology, Engineering, Mathematics) classroom by sustaining student involvement, leading to improved retention of the material (Ketsman et al., 2018).

In addition, interactive educational videos, if used as a scaffold, could aid in reducing the extraneous cognitive load and promote an increase in germane cognitive load when intrinsic cognitive load is minimized in a digital game-based learning (DGBL) environment (Liao et al., 2019). This is because educational videos can enhance the cognitive resources for constructing a conceptual model, enabling an increased cognitive capacity to progress in the DGBL. Hence, if instructional sequences are adequately incorporated into educational videos, it could facilitate an increase germane load that is much needed for the cognitive processing of schema construction.

Better student engagement was evident with the use of interactive educational videos. According to Zhang et al. (2006) on undergraduate students from multiple departments, the interactive nature of educational videos promoted engagement, active participation, responsiveness, and involvement of students as it empowered students to focus on educational content through dynamic interactions, facilitating their full attention. The study by Maziriri et al. (2020) suggests that university students' perceived use of YouTube videos for academic tutorials positively influenced their attitudes towards such tutorials. In addition, students who perceived YouTube as an easily accessible platform are more likely to have a positive inclination towards continued usage, which in turn, positively affects their behavioural intention to use it actively.

Using educational videos have also been found to improve students' satisfaction of the course and their learning experiences. For instance, Hsin and Cigas (2013) found that the utilization of video mini lectures in an introductory computer science class resulted in increased student satisfaction with the course, higher completion rates, and a slight improvement in students' course grades. In another study by Wells et al. (2012), the integration of video tutorials in the university setting over the course of three years found that well-designed, assessment-centred video tutorials, when readily accessible to students, held the promise of enhancing both student satisfaction and academic performance. This was achieved by affording students the flexibility to learn at their preferred pace, aligning with their unique learning styles and needs. More recently, Preradović et al. (2020) discovered that while there was no statistically significant difference in students' procedural learning outcomes when comparing students using demonstration videos and interactive videos, students using interactive videos expressed greater satisfaction as they perceived the interactive videos as more informative compared to demonstration videos.

In terms of cultivating interest in the content, educational videos have been shown to improve their interest to learn the content. For example, June et al. (2014) demonstrated that in addition to increased student participation and engagement, YouTube videos were enjoyable and captivating for Malaysian university students. Students held a favourable perception of using the YouTube videos and were regarded as effective in maintaining and sparking sustained interest in the topics under discussion.

**User Engagement**

More generally, engagement can be seen a mechanism to aid individuals in monitoring and attaining their objectives, to experience immersion in artistic or social contexts, to prompt inclusivity and democratic values, and to attain personal aspirations (O'Brien et al., 2022). Specifically, within the context of a user interacting with technology, user engagement (UE) is a facet of the user experience distinguished by the extent of an individual's cognitive, temporal, emotional, and behavioural commitment during his or her interaction with a digital system (O'Brien, 2016). It represents both the process and outcome of a person's interactions with technology (O'Brien & MacLean, 2009). By defining UE as an attribute, it offers the benefit of aiding researchers in implementing design principles or developing measurement tools for user experience (O'Brien et al., 2018).

UE goes beyond mere user satisfaction. It is widely held that the capacity to engage and maintain engagement within digital environments can result in favourable outcomes such as citizen inquiry, participation, e-health, web search, e-learning, and much more (O'Brien et al., 2018). Every digital environment possesses distinctive technological affordances that interact with users' motivations in the pursuit of desirable outcomes, therefore, it can be said that UE is highly dependent on the technological context in which the user interacts in (O'Brien et al., 2018).

**Effect of Cognitive Load on User Engagement and Learning Satisfaction**

Cognitive load originally stems from mental workload and is primarily examined through the psychological, physiological, and cognitive lenses. It delves into how an individual's overall workload affects their ability to perform a specific task and the advantages associated with their information processing (Paas et al., 2010). There are three facets of cognitive load, namely, intrinsic, extraneous, and germane cognitive load (Sweller et al., 1998). Intrinsic load concerns the inherent complexity and difficulty level of the educational material, while extraneous load pertains to the way the material is presented which are influenced by a variety of design choices. Germane load, on the other hand, refers to cognitive capacity used when constructing schemas. As envisioned by Chandler and Sweller (1991), the thoughtful crafting of teaching materials and instructional design have the potential to lessen a learner's extraneous cognitive load, thereby expanding their working memory resources for construction, ultimately resulting in an increase in their germane load.

Research has shown that extraneous and germane load are negatively related suggesting that unclear instruction can lead to reduced learning in e-learning settings, especially when instruction necessitates unnecessary processing due to the inclusion of irrelevant or redundant material (Costley et al., 2021; Mayer & Moreno, 2003). Regarding the negative relation between extraneous and germane load, Costley et al. (2021) found that the way learners view educational videos can positively mediate this relationship. In other words, viewing strategies can help mitigate the adverse impact of extraneous load on a learner's germane load by making more effective use of their cognitive resources, despite potential distractions or extraneous elements in the videos.

Research has also demonstrated that educational videos have the potential to reduce learners' cognitive load, thereby enhancing engagement and satisfaction in learning. For example, Altinpulluk et al. (2020) found that when educational videos were segmented into meaningful parts, cognitive load is reduced, freeing up working memory resources for the processing of information. This in turn allowed learners to participate more in the learning processes, utilise the materials more efficiently, and increased learners' satisfaction levels. In another study by Vesga et al. (2021), a higher level of frustration (a facet of cognitive load) predicted a decrease in student engagement with the learning tasks. Furthermore, effort (a component of cognitive load) was found to have a significant positive impact on students' cognitive engagement, suggesting that a perceived level of effort invested in their interactions within the virtual learning environment, over and above the effort put into the learning tasks. Using perceived task difficulty, a closely related concept to cognitive load, O'Brien et al. (2020) found that the increased complexity experienced due to task manipulation led to the perception that more demanding tasks were less engaging. Collectively, the above findings demonstrate that cognitive load can have an impact on learner engagement and satisfaction.

**Effect of Task Value on User Engagement and Learning Satisfaction**

Task value concerns the learner's assessment of the level of interest, significance, and utility of a task, essentially reflecting their personal perspective of the task's worth and relevance (i.e., what do I think of this task) (Pintrich et al., 1991). Tasks that were perceived as more interesting were found to have resulted in greater user engagement. For example, in a study of the effects of task on search engagement, O'Brien et al. (2020) found that post-task interest levels were correlated with higher engagement, with different task topics receiving varying levels of interest ratings, demonstrating that task topics can influence the degree of user engagement.

Additionally, task value was found to relate to learning satisfaction. Joo et al. (2013) for example, showed that learners' perception of the value of a task emerged as a crucial predictor of satisfaction, achievement, and persistence from a sample of 897 learners enrolled in an online university located in South Korea. Learners with higher levels of perceived self-efficacy, task value, and internal locus of control were generally more satisfied with the online university course. In another study by Hong et al. (2016), path analysis showed a significant positive direct path from interest in learning with social media to learning satisfaction with social media, implying that higher interest in learning predicted higher learning satisfaction. Similar results were also observed by Gumelar et al. (2021), where higher task value led to higher satisfaction with online learning in 516 Indonesian university students. In addition, Gumelar and colleagues discovered that the positive relationship between task value and satisfaction was mediated by students' perception of online learning, suggesting that the way learners perceived their online learning could explain why higher task value resulted in higher satisfaction with online learning.

Despite evidence of the positive relations between task value and learner engagement and satisfaction, there appears to be limited research on understanding how tasks drive students to interact with the digital systems that influence the levels of user engagement

(O’Brien et al., 2020). Most of the research into user engagement has primarily centred on assessing user engagement in various digital contexts (e.g., O’Brien, 2018; O’Brien & Cairns, 2016), as well as examining how content characteristics (e.g., positive or negative sentiment, interesting or uninteresting) and system features (e.g., use of multimedia, aesthetic appeal, interactivity) contribute to creating engaging experiences (for a comprehensive overview, refer to O’Brien & McKay, 2018).

**Effect of User Engagement on Learning Satisfaction**

Learner satisfaction pertains to the favourable emotions or positive sentiments that students have regarding their learning experiences and is usually measured after the learning activity (Keller, 1983). Research has shown that higher engagement is typically associated with higher learning satisfaction. In a study by Barker et al. (2014), the state of flow, conceptualised as enjoyment and engagement, was found to predict website satisfaction significantly positively, perception of concentrated and unintentional knowledge acquisition. When compared across respondent groups for content communities, e-commerce, and social networking sites, no significant differences were observed in the positive relationship between flow and website satisfaction. Chen (2022) found that student attitudes towards using a game-based learning application was a robust predictor for course engagement and motivation for learning translation, suggesting that the better students engaged with the educational tool, the more likely they will be engaged in the course, the more extrinsically motivated they will be, and consequently, the better their satisfaction with learning.

**Summary and Conceptual Model**

In summary, the above literature review has shed light on the relations between (1) cognitive load and user engagement, (2) cognitive load and learning satisfaction, (3) task value and user engagement, (4) task value and learning satisfaction, and (5) user engagement and learning satisfaction, in the context of multimedia use. Furthermore, we have discussed what interactive educational videos are and how they promote task value, learning engagement, satisfaction, and reduce cognitive load.

Given the limited prior research that comprehensively investigates the interplay of cognitive load, user engagement, learning satisfaction, and task value in interactive educational videos (cf. Altinpulluk et al., 2020), our study primarily takes an exploratory approach. Consequently, we have refrained from putting forward specific hypotheses and, instead, have developed a conceptual model (see Figure 1) rooted in the findings from our literature review. We also extend the UEF proposed by Suh and Cheung (2019) to include cognitive load as a contributing factor towards user engagement.

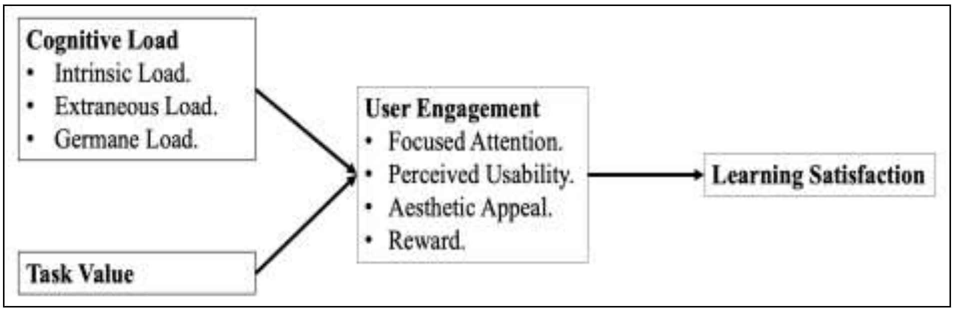


Figure 1
Conceptual model for the present study.

**The Present Study**

The primary aims of this exploratory study are delineated as follows. First, we examine the mediating effect of user engagement on the relationship between (a) cognitive load and learner satisfaction, and (b) task value and learning satisfaction. Second, we investigate if user engagement moderates the relation between cognitive load and learning satisfaction, and similarly, between task value and learning satisfaction. The corresponding research questions for this study are listed in Table 1 below.

Table 1
Research Questions

| | |
|---|---|
| RQ1. | Does user engagement mediate the relationship between the antecedents and learning satisfaction?<br>RQ1.1. Does user engagement (i.e., FA, PU, AE, RW) mediate the relationship between cognitive load (i.e., intrinsic, extraneous, germane) and learning satisfaction?<br>RQ1.2. Does user engagement (i.e., FA, PU, AE, RW) mediate the relationship between task value and learning satisfaction? |
| RQ2. | Does user engagement moderate the relationship between the antecedents and learning satisfaction?<br>RQ2.1. Does user engagement (i.e., FA, PU, AE, RW) moderate the relationship between cognitive load (i.e., intrinsic, extraneous, germane) and learning satisfaction?<br>RQ2.2. Does user engagement (i.e., FA, PU, AE, RW) moderate the relationship between task value and learning satisfaction? |

**METHOD**

**Design of Interactive Educational Videos**

In designing interactive educational videos for year-one Engineering students taking foundational mathematics and physics modules at our university, we drew upon Mayer's (2017) widely used 12 principles for multimedia learning. Our approach focused on optimizing the interactive educational videos to reduce unnecessary extraneous cognitive load, adhering to five specific principles: coherence (i.e., eliminating extraneous content), signaling (i.e., highlighting essential material), redundancy (i.e., avoiding simultaneous on-screen text with graphics and narration), spatial contiguity (i.e., aligning on-screen text with relevant graphics), and temporal contiguity (i.e., presenting narration and graphics simultaneously). To enhance cognitive processing efficiency, we employed three research-backed principles:

segmenting (i.e., delivering content in small, user-paced segments), pre-training (i.e., offering a brief lesson on key concepts before video content), and modality (i.e., conveying words through spoken narration). Furthermore, to stimulate active cognitive engagement, we integrated the principles of personalization (i.e., delivering content in conversational style), voice (i.e., using human voice rather than machine-like one), and embodiment (i.e., incorporating human-like gestures and movements).

**Participants and Procedures**

Prior to data collection, our study was approved by the university's institutional review board (IRB) for ethics clearance (IRB number RECAS-0060). Using a cross-sectional survey research design, we approached an entire cohort of approximately 800 year-one Engineering students from various Engineering programmes (e.g., Mechanical Engineering, Aerospace Engineering) taking foundational mathematics and physics modules at our university during a trimester, lasting from May 2023 to August 2023. These students would have experience using our curated interactive educational videos. Through the module leaders and coordinators, we invited these students to answer a self-report questionnaire consisting of items pertaining to the latent variables of cognitive load, task value, user engagement, and learning satisfaction. The survey was hosted on the online Qualtrics platform for freshmen to conveniently access and complete. Participation was voluntary and time (about 15 minutes) was set aside during the tutorial sessions for students to respond to the survey.

The present study utilized a convenient sampling method for the selection of participants. Of the roughly 800 year-one students that we approached, 49 students voluntarily participated in the survey, yielding a participation rate of about 6.13%. We acknowledge that the participation rate is relatively low and advise caution when attempting to generalize our findings across contexts. Due to the limited resources (e.g., manpower) and time constraints (e.g., two-week period to collect the data), we were unable to garner higher levels of participation for the study. Nevertheless, we believe that the findings from our convenience sample of 49 students will still be meaningful in addressing the research questions for the present study. As highlighted in THE PRESENT STUDY, our study takes an exploratory approach and hence using a convenience sample was deemed appropriate. We anticipate that the results can serve as a foundation for future, more extensive research. No demographic information (e.g., gender, age) was collected owing to the exploratory nature of this study and our primary focus of examining the relations between the constructs in the conceptual model.

**Instruments**

The measurement instruments in this study were adapted from four well-established scales: (a) Cognitive Load Scale (CLS) (Leppink et al., 2013), (b) Task Value Scale (TVS) (Pintrich et al., 1991), (c) User Engagement Scale – Short Form (UES-SF) (O-Brien et al., 2018), and (d) Learning Satisfaction Scale (LSS) (Nagy, 2018). The CLS contains three subscales of intrinsic load (3 items), extraneous load (3 items), and germane load (4 items), while the TVS contains six items and assesses a learner's assessment of the level of interest, significance, and utility of a task (i.e., what do I think of this task). On the other hand, the UES-SF comprises 12 items with three items measuring each of the four facets of focused attention (FA), perceived usability (PU), aesthetic appeal (AE), and reward (RW). Prior to the present study, we found good to acceptable Cronbach's alpha for all dimensions, except for FA, and a reasonable model fit to the data for a correlated four-factor model, in a preliminary validation study of the UES-SF (see Kok et al., 2023). Finally, learning satisfaction was measured using four items. All the above scales have shown reasonable internal reliabilities in previous studies. The items in the above scales were rated by participants on a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

### Data Analysis Strategy

All statistical analyses were performed using the Statistical Package for the Social Sciences (SPSS) software version 27.0 (IBM Corporation, 2020). To examine the internal reliability of all latent variables, we computed Cronbach's alpha coefficients. The means, standard deviations, and bivariate correlations (via Pearson correlation coefficients) of all study variables were also estimated. Preliminary tests were conducted to examine if the statistical assumptions of independence of observations, linearity, homoscedasticity, multicollinearity, presence of outliers, and normality were met. Multiple linear regression was used to test the predictive value of cognitive load (i.e., intrinsic, extraneous, germane) and task value on user engagement and learning satisfaction, respectively, as well as the predictive effects of user engagement on learning satisfaction. Based on significant standardized regression coefficients obtained inthe multiple linear regression analyses, we examined the mediation effect of user engagement on the relationship between the antecedents and learning satisfaction (RQ1) via Baron and Kenny's (1986) approach. To examine the moderating effect of user engagement on the relationship between the antecedents and learning satisfaction (RQ2), we used hierarchical linear regression analysis.

## FINDINGS

### Internal Reliabilities of Latent Variables

The internal consistencies of the latent variables were evaluated using Cronbach's alpha, determined based on the number of items in the scale and the average inter-correlation among these items (Nunnally, 1978). We adhered to George and Mallery's (2003) classification, wherein alpha values $\geq .90$ are excellent, $\geq .80$ are good, $\geq .70$ are acceptable, $\geq .60$ are questionable, $\geq .50$ are poor, and $< .50$ are unacceptable. The alpha values for the latent constructs were as follows: intrinsic load ($\alpha = .67$), extraneous load ($\alpha = .68$), germane load ($\alpha = .88$), task value ($\alpha = .90$), focused attention ($\alpha = .64$), perceived usability ($\alpha = .67$), aesthetic appeal ($\alpha = .80$), reward ($\alpha = .94$), and learning satisfaction ($\alpha = .82$).

### Bivariate Correlations among Latent Variables

The bivariate correlations between the latent variables are presented in Table 3 below. All correlation coefficients were significant, except between perceived usability and (a) germane load, (b) task value, (c) focused attention, (d) aesthetic appeal, (e) reward, and (f) learning satisfaction. Majority of the significant correlation coefficients were moderate (≥ |.30|) to strong (≥ |.50|), except for extraneous load and germane load ($r$ = .28, $p$ < .05).

Table 3
Means, standard deviation (SD), and bivariate correlations for all latent variables

| Latent Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 3.48 | 3.18 | 3.69 | 3.72 | 3.65 | 3.38 | 2.76 | 3.44 | 3.57 |
| SD | .71 | .82 | .75 | .67 | .72 | .80 | .79 | .79 | .87 |
| 1. IL | --- | | | | | | | | |
| 2. EL | .68** | --- | | | | | | | |
| 3. GL | .39** | .28* | --- | | | | | | |
| 4. TV | .52** | .30* | .92** | --- | | | | | |
| 5. FA | .56** | .49** | .76** | .77** | --- | | | | |
| 6. PU | –.45** | –.71** | –.05 | –.08 | –.27 | --- | | | |
| 7. AE | .60** | .39** | .69** | .64** | .77** | –.19 | --- | | |
| 8. RW | .47** | .32* | .92** | .88** | .84** | .00 | .81** | --- | |
| 9. LS | .64** | .50** | .79** | .80** | .77** | –.23 | .82** | .80** | --- |

**NOTE:** IL = Intrinsic Load, EL = Extraneous Load, GL = Germane Load, TV = Task Value, FA = Focused Attention, PU = Perceived Usability, AE = Aesthetic Appeal, RW = Reward, LS = Learning Satisfaction.
**NOTE:** N = 49, *$p$ < .05, **$p$ < .01. Statistically significant correlations appear in bold.

### Predictive Relationships between User Engagement, Antecedents, and Outcome

RQ1 is concerned with the predictive relations amongst user engagement, its antecedents of cognitive load and task value, and the outcome of learning satisfaction. Multiple regression analyses were conducted for RQ1.1, RQ1.2, and RQ1.3.

The results revealed that intrinsic load significantly and positively predicted aesthetic appeal (β = .41, $p$ < .01) and learning satisfaction (β = .32, $p$ < .01). Extraneous load, on the other hand, only significantly and negatively predicted perceived usability (β = −.75, $p$ < .001). Meanwhile, germane load showed significant and positive predictions with focused attention (β = .64, $p$ < .001), aesthetic appeal (β = .54, $p$ < .001), reward (β = .87, $p$ < .001), and learning satisfaction (β = .63, $p$ < .001). Task value significantly and positively predicted learning satisfaction (β = .80, $p$ < .001) and all aspects of user engagement except for perceived usability (β = −.08, $p$ = .606). Finally, aesthetic appeal (β = .39, $p$ < .01) and reward (β = .43, $p$ < .05) were significant and positive predictors of learning satisfaction.

### Mediating Effect of User Engagement on Relationship between Antecedents and Outcome (RQ1)

Based on the significant standardized regression weights, we proceeded to examine the mediating effect of specific components of user engagement on the relationships between the antecedents (i.e., cognitive load, task value) and outcome (i.e., learning satisfaction). Four possible mediation models were analyzed due to the presence of significant relations amongst the predictor, mediator, and outcome variables in each model. Table 4 below summarizes the results obtained for each mediation model.

Table 4
Results of mediation models

| Model | Predictor | Mediator | Outcome | Result |
|---|---|---|---|---|
| MED1 | Germane Load | Aesthetic Appeal | Learning Satisfaction | Partial mediation effect |
| MED2 | Germane Load | Reward | Learning Satisfaction | Full mediation effect |
| MED3 | Task Value | Aesthetic Appeal | Learning Satisfaction | Partial mediation effect |
| MED4 | Task Value | Reward | Learning Satisfaction | Partial mediation effect |

In analyzing the mediating effect of the mediator on the relationship between the predictor and the outcome variable, we first examined how well the predictor and mediator explained variance in the dependent variable (i.e., learning satisfaction) via hierarchical multiple regression analysis. Two steps were involved. First, the predictor was entered into the regression model predicting learning satisfaction. Second, the mediator was added into the model. To ascertain whether a mediating effect was present, the standardized regression coefficients (β) of the predictor in the first step were compared with that obtained in the second step. According to Baron and Kenny (1986), this approach is considered an indispensable requirement to determine if there was the presence of a mediator. A full mediation effect is present if the direct β from the predictor to the outcome drops in magnitude and becomes non-significant from step one to step two in the regression analysis. On the other hand, if the direct β reduces in magnitude but is still significant in step two, then a partial mediation effect is present. In contrast, if no reduction of β is observed and remains significant in step two, then there is no evidence to support a mediation effect.

We further estimated the effect size of the mediator variables by calculating the product of two regression coefficients, between the predictor and mediator, in accordance with Sobel's (1982) approach. To interpret the effect sizes obtained, we adopted standards recommended by Cohen (1988), where .10 indicates a small effect size, .30 a medium effect size, and .50 a large effect size. In addition, to confirm if the indirect effect from the predictor to outcome via the mediator was significant, we examined the *p*-value of the indirect effect using Sobel's (1982) approach and the bootstrapped interval range of the indirect effect using the process procedure by Preacher and Hayes (2004). Alpha levels were all set at $p < .05$.

In summary, the results presented in Table 4 suggest the following:

1. Better aesthetic appeal (e.g., appealed to senses, aesthetically appealing, images that aroused interest) of the interactive educational videos can partially explain why higher germane load (e.g., enhanced knowledge and understanding of topics, definitions, concepts, and formulas) was associated with higher learning satisfaction.

2. A greater sense of reward (e.g., videos were worthwhile watching, experience was rewarding, interesting) derived from viewing the interactive educational videos can fully explain why higher germane load was associated with higher learning satisfaction.

3. Better aesthetic appeal of the interactive educational videos can partially explain why higher task value (e.g., importance, usefulness of videos) was associated with higher learning satisfaction.

4. A greater sense of reward derived from viewing the interactive educational videos can partially explain why higher task value was associated with higher learning satisfaction.

**Moderating Effect of User Engagement on Relationship between Antecedents and Outcome (RQ2)**

To examine if user engagement had a moderating effect on the relationship between the antecedents (i.e., cognitive load, task value) and outcome (i.e., learning satisfaction), we first checked if significant correlations existed amongst these variables. Based on that, four moderation models were drawn up and analysed in accordance with the hierarchical regression method proposed by Baron and Kenny (1986). The results of these moderation models are summarized in Table 5 below.

Table 5
Results of moderation models

| Model | Predictor | Moderator | Interaction Term | Outcome | Result |
|---|---|---|---|---|---|
| MOD1 | Germane Load | Aesthetic Appeal | GL × AE | Learning Satisfaction | No moderation effect |
| MOD2 | Germane Load | Reward | GL × RW | Learning Satisfaction | Moderation effect |
| MOD3 | Task Value | Aesthetic Appeal | TV × AE | Learning Satisfaction | No moderation effect |
| MOD4 | Task Value | Reward | TV × RW | Learning Satisfaction | Moderation effect |

**NOTE:** Germane Load = GL, Aesthetic Appeal = AE, Task Value = TV, Reward = RW.

As moderation effects were detected for MOD2 and MOD4, we will therefore only elaborate on the steps taken and results for both these models. For MOD2, the predictor (i.e., germane load) was added in step one of the hierarchical regression analysis. This was followed by the addition of the moderator (i.e., reward) in step two. MOD2b explained 65.8% of variance in learning satisfaction, 4.2% higher than that of MOD2a. Germane load was a significant predictor of learning satisfaction in MOD2a but became non-significant predictor in MOD2b. Reward, on the other hand, was a significant predictor of learning satisfaction in MOD2b. In step three, the interaction term, GL × RW, was added. This resulted in a 7.9% increase in explained variance from MOD2b to MOD2c, culminating in a total explained variance of 73.7% in learning satisfaction. The $R^2$ increased over the moderation models, from 61.6% in MOD2a, to 65.8% in MOD2b, and finally to 73.7% in MOD2c. Although the predictor (i.e., germane load) was not statistically significant in MOD2c, however, the moderator and interaction term were statistically significant. Table 6 illustrates the hierarchical regression analysis for MOD2a, MOD2b, and MOD2c.

Table 6
Moderating effect of reward on the relationship between germane load and learning satisfaction

| | MOD2a | | | MOD2b | | | MOD2c | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | B | SE | β | B | SE | β | B | SE | β |
| Germane Load | .75 | .09 | .79** | .29 | .21 | .31 | .34 | .19 | .35 |
| Reward | | | | .43 | .18 | .52* | .49 | .16 | .59** |
| GL × RW | | | | | | | .19 | .05 | .30** |
| $R^2$ | .62 | | | .66 | | | .74 | | |
| Adjusted $R^2$ | .61 | | | .64 | | | .72 | | |
| Change in $R^2$ | .62 | | | .04 | | | .08 | | |
| F for change in $R^2$ | 75.39** | | | 5.60* | | | 13.60** | | |

**p* < .05 (two-tailed), ***p* < .01 (two-tailed)
B = unstandardised regression coefficient, SE = standard error, β = standardised regression coefficient.
Germane Load = GL, Reward = RW.

The interaction plot involving the moderating effect of reward on germane load and learning satisfaction is displayed in Figure 2. Reward was categorized into three levels, namely, low (RWlow < RWmean – 0.5 × SD), moderate (RWmean – 0.5 × SD ≤ RWmoderate ≤ RWmean + 0.5 × SD), and high (RWhigh > RWmean + 0.5 × SD). Based on Figure 2, it can be concluded that at high levels of reward (e.g., interactive educational videos were worthwhile watching, experience was rewarding, interesting), the positive effect of germane load on learning satisfaction was the strongest. For students who found the interactive educational videos moderately rewarding, the positive effect of germane load on learning satisfaction was moderate. Finally, at low levels of reward, the positive effect of germane load on learning satisfaction was the weakest. These results suggest that the extent to which students found the interactive educational videos rewarding is paramount in strengthening the positive effect of enhancing knowledge and understanding of foundational mathematics and physics concepts (i.e., germane load) on learning satisfaction.

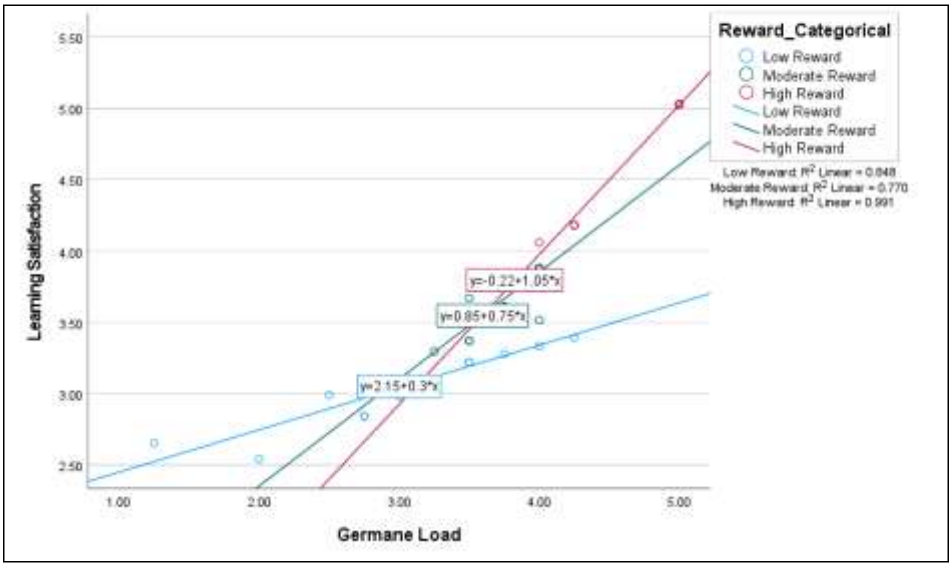


Figure 2
Interacting plot of reward on the relationship between germane load and learning satisfaction

In MOD4a, the predictor (i.e., task value) was introduced during the first step of the hierarchical regression analysis. Subsequently, in the second step, we included the moderator variable, which is reward (MOD4b). MOD4b explained 68.3% of the variance in learning satisfaction, 4.2% higher than in MOD4a. In step three (MOD4c), the interaction term, TV × RW, was added. This resulted in a 4.8% increase in explained variance from MOD4b to MOD4c, accounting for a total variance of 73.0% in learning satisfaction. The $R^2$ values increased progressively across the moderation models, from 64.1% in MOD4a, to 68.3% in MOD4b, and finally to 73.0% in MOD4c. All the variables were statistically significant in MOD4a, MOD4b, and MOD4c.

Table 7
Moderating effect of reward on the relationship between task value and learning satisfaction

| | MOD4a | | | MOD4b | | | MOD4c | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | B | SE | β | B | SE | β | B | SE | β |
| Task Value | .86 | .09 | .80** | .45 | .19 | .42* | .44 | .18 | .41* |
| Reward | | | | .36 | .15 | .43* | .42 | .14 | .52** |
| TV × RW | | | | | | | .17 | .06 | .23** |
| $R^2$ | .64 | | | .68 | | | .73 | | |
| Adjusted $R^2$ | .63 | | | .67 | | | .71 | | |
| Change in $R^2$ | .64 | | | .04 | | | .05 | | |
| F for change in $R^2$ | 83.74** | | | 6.10* | | | 8.00** | | |

*$p < .05$ (two-tailed), **$p < .01$ (two-tailed)
B = unstandardised regression coefficient, SE = standard error, β = standardised regression coefficient.
Task Value = TV, Reward = RW.

Figure 3 presents the interaction plot involving the moderating effect of reward on task value and learning satisfaction. Reward was categorized into low, moderate, and high, as mentioned above. Based on Figure 3, we can conclude that at high levels of reward (e.g., interactive educational videos were worthwhile watching, experience was reward, interesting), the positive effect of task value on learning satisfaction was the strongest. For students who found the interactive educational videos moderately rewarding, the positive effect of task value on learning satisfaction was moderate. Finally, at low levels of reward, the positive effect of task value on learning satisfaction was the weakest. These results suggest that the extent to which students found the interactive educational videos rewarding is paramount in strengthening the positive effect of how interesting, important, and useful students found the content covered in the interactive educational videos (i.e., task value) on learning satisfaction.

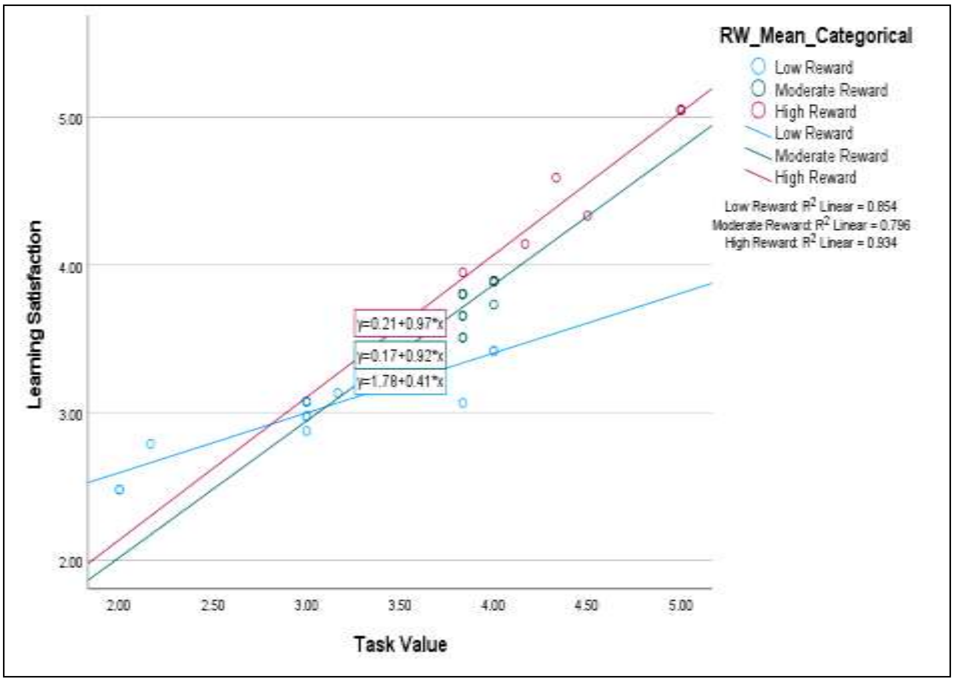


Figure 3
Interacting plot of reward on the relationship between task value and learning satisfaction.

## DISCUSSION

### Discussion of Main Findings

In summary, we found that reward fully mediated the relationship between germane load and learning satisfaction. In addition, reward was discovered to have moderated the relationship between (a) germane load and learning satisfaction, and (b) task value and learning satisfaction.

The fact that reward fully mediated the relation between germane load and learning satisfaction suggests that having a rewarding and interesting experience when using the interactive educational videos could explain why students who felt that the videos enhanced their understanding and knowledge of key foundational mathematics concepts had better learning satisfaction. Prior research had established that educational videos could reduce students' cognitive load, enhancing engagement and satisfaction in learning (Altinpulluk et al., 2020; O'Brien et al., 2020; Vesga et al., 2021). However, to the best of our knowledge, there appears to be little to no prior research studying how reward functions as a mediator in the relationship between germane load and learning satisfaction. It could be that when learners engage deeply with the videos to understand the content, they may experience a sense of accomplishment and mastery. This sense of achievement acts as a reward, contributing to an increase in learning satisfaction. Hence, incorporating rewarding experiences in the videos can enhance the satisfaction learners derive from the content, possibly motivating them to engage more deeply with the material in the videos. To understand how rewarding experiences can be enhanced, we suggest that future research be undertaken to examine, at a finer grain level, which specific aspects of the videos (e.g., coherence of content, visual presentation of content, embedded quizzes), contribute to the sense of reward felt by students and subsequently, how these aspects can be enriched.

In addition, we observed that reward moderated the relationship between (a) germane load and learning satisfaction, and (b) task value and learning satisfaction. This suggests that the extent to which students found the interactive educational videos rewarding influences the positive effect of enhancing knowledge and understanding of foundational concepts on learning satisfaction. Specifically, we found that students who found the videos very rewarding (e.g., worthwhile watching, interested in watching, rewarding experience) exhibited the strongest positive effect of the videos enhancing knowledge and understanding of topics and concepts on satisfaction with learning from the videos, as compared to those who found the videos to be moderately or lowly rewarding. It is possible that the rewarding experience derived from using the videos served as powerful motivators, encouraging learners to actively engage with the content in the videos. When learners are motivated, they could have approached learning the content in the videos with a more positive attitude, thereby encouraging them to delve deeper into understanding of topics and concepts illustrated through the videos, thus contributing to higher levels of satisfaction.

Regarding the moderating effect of reward on the relationship between task value and learning satisfaction, it suggests that the extent to which students found the interactive educational videos rewarding influences the positive effect of task value (i.e., importance, usefulness, interest) on learning satisfaction. Our findings show that students who found the videos very rewarding (e.g., worthwhile watching, interested in watching, rewarding experience) exhibited the strongest positive effect of valuing the videos in terms of importance, usefulness, and interest on satisfaction with learning from the videos, as compared to those who found the videos to be moderately or lowly rewarding. A possible explanation for this moderation effect is a rewarding experience when engaging with the videos can influence learners' perceptions of the value of the educational content. When learners value the content in the videos, it can contribute to better learning satisfaction with the use of the videos. While earlier research has found positive relations between task value and learning satisfaction (Hong et al., 2016; Gumelar et al., 2021; Joo et al., 2013), there appears to be a paucity of studies examining reward as a moderator between both variables. Hence, our study is likely among the first to investigate this moderating effect.

### Theoretical and Practical Implications

The findings provide empirical evidence for the existence of our proposed conceptual model (see Figure 2). To the best of our knowledge, this study was the first to explore the mediating and moderating effects of user engagement on the relationship between the antecedents (i.e., intrinsic load, extraneous load, germane load, and task value) and learning satisfaction. Notably, we found that reward moderated the positive relationship between (a) germane load and learning satisfaction, and (b) task value and learning satisfaction. Furthermore, we noticed that reward fully mediated the relationship between germane load and learning satisfaction. It is therefore important to incorporate and enhance rewarding experiences in the interactive educational videos to strengthen the relations between germane load, task value, and learning satisfaction. According to O'Brien et al. (2018), reward refers to students' perceptions of the worthwhileness of the videos, their interest in watching the videos, and the extent to which they found the videos to be rewarding. To imbue a greater sense of reward, the enhanced interaction feature of embedded quiz questions could be further refined in our existing interactive educational videos to include immediate feedback with detailed explanations (Rice et al., 2019).

### Limitations and Future Research

There are several limitations in the present study. First, our study adopted a cross-sectional design, hence we were unable to examine the causal relationships among the latent variables in this study. Instead, we were only able to provide a snapshot of the relations between the antecedents, user engagement, and learning satisfaction. For future research, we suggest the use of a longitudinal design where data is collected over a few time points to verify the findings. Second, due to the exploratory nature of this study and the practical constraints faced, we resorted to convenience sampling to collect the survey data. This sampling method is, however, prone to selection bias. In future research, probability sampling could be used to reduce the sampling error and increase the value of the study outcomes. Third, the reliance on self-report questionnaires in this study raises the possibility of recall and reporting bias, resulting in the confounding influence on the associations amongst the study variables. Future research could consider the triangulation of multimodal methods of data collection such as interviews and log data from the interactive educational videos.

## CONCLUSION

Overall, our findings provide evidence for the mediation and moderation effects of user engagement in the relationship between the antecedents and learning satisfaction. Reward fully mediated the relationship between germane load and learning satisfaction and moderated the relationship between (a) germane load and learning satisfaction, and

(b) task value and learning satisfaction. Thus, our findings highlight the importance of creating rewarding experiences when designing interactive educational videos. To sum up, our study contributes to the extant literature on user engagement in the following ways by: (a) extending Suh and Cheung's (2019) framework to incorporate cognitive load as an antecedent, and (b) examining the mediating and moderating effects of user engagement components in the relationship between the antecedents and learning satisfaction.

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