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Comparing cognitive load levels among family members of the critically ill exposed to electronic decision aids

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ABSTRACT

Cognitive load predicts one's ability to process information and learn from decision support interventions. The present study compared intrinsic and extraneous cognitive load levels resulting from exposure to two different electronic decision aids. A convenience sample of ninety-seven surrogate decision makers for critically ill patients were randomly assigned to receive either a single dose of a video-based or avatar-based decision aid. Intrinsic and extraneous cognitive load levels among recipients of the video-based decision support resource were lower than recipients of the avatar-based decision support resource. After controlling for age, the observed differences in intrinsic cognitive load were not significantly different, whereas the observed differences in extraneous cognitive load remained. Extraneous cognitive load is a modifiable factor to consider for future developers of decision support interventions that may determine the efficacy of efforts to support patients and family members with decision making.

1. Introduction

Approximately 80% of patients in the intensive care unit (ICU) lack decision- making capacity (Pisani, McNicoll, & Inouye, 2003). When patients cannot make their own healthcare decisions, critical care clinicians rely upon family members and loved ones to serve as surrogate decision makers (SDMs). SDMs for the critically ill are responsible for making complex treatment and end-of-life decisions – often with limited knowledge of the patient's care preferences (Kon, Davidson, Morrison, Danis, & White, 2016; Rodriguez et al., 2008). Critical care clinicians have tested an assortment of decision support interventions to assist SDMs with these complex decisions. Predominantly, these interventions have focused on enhancing knowledge or communication. However, they demonstrate limited effectiveness (Pignatiello, Hickman Jr, & Hetland, 2018).

These shortcomings may be unrelated to the actual content of the interventions. Netzer and Sullivan (2014) posit that the demands placed on SDMs may compromise their ability to process information necessary to make decisions. For example, SDMs must be able to comprehend highly complex information, often in states of intense emotional distress, fatigue, and sleep deprivation (Netzer & Sullivan, 2014; White, 2011). These factors may overwhelm SDM cognitive processing systems and may potentially mitigate the effectiveness of supportive interventions (Netzer & Sullivan, 2014). Thus, clinicians and scientists must consider the demands supportive interventions place on SDM cognitive systems.

Cognitive Load describes the demand placed on SDM cognitive systems from decision support interventions (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). There are two types of cognitive load: intrinsic and extraneous. Intrinsic cognitive load (ICL) refers to the load induced by the complexity of material being presented and the number of informational elements that must be simultaneously processed to comprehend said information (Sweller, 2010). Extraneous cognitive load (ECL) is determined by *how* material is presented. To maximize the effectiveness of decision support interventions, ECL should be minimized and ICL should be optimized to maintain SDM engagement

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without surpassing his or her knowledge base and capacity to process multiple elements (Chen, Castro-Alonso, Paas, & Sweller, 2018; Leppink, 2017; Leppink, Paas, Van Gog, van Der Vleuten, & Van Merrienboer, 2014). Therefore, measuring SDM cognitive load can inform the unique ways in which decision support interventions burden their cognitive systems and impair their ability to process information.

Empirical evidence of cognitive load measurement within nursing and other healthcare domains is limited. For instance, cognitive load measurement in healthcare domains predominantly occurs within medical procedure training for clinicians (Aldekhyl, Cavalcanti, & Naismith, 2018; Chen et al., 2018; Hadie & Yusoff, 2016). Furthermore, the majority of studies that measure cognitive load use the National Aeronautics and Space Administration Task Load Index (NASA-TLX) or Paas's (1992) cognitive load instrument. However, the NASA-TLX is a proxy measure of cognitive load, and Paas's (1992) instrument does not measure cognitive load domains (i.e., ICL and ECL). Of the healthcare related studies that use instruments to measure cognitive load domains, none have compared the cognitive load elicited by various types of educational resources (Aldekhyl et al., 2018; Chen et al., 2018; Hadie & Yusoff, 2016). Evaluation of cognitive levels can inform an SDM's unique cognitive response to different types of decision support interventions.

Cognitive load may influence the effectiveness of decision support interventions for SDMs of the critically ill. If ICL is not optimized and ECL is too high, SDMs may fail to process vital information necessary for them to make informed and rational decisions for their critically ill loved one. As a result, patients may receive care inconsistent with their preferences and SDMs may be vulnerable to prolonged psychiatric illness (Davidson, Jones, & Bienvenu, 2012; White, 2011). Currently, there is no evidence comparing the cognitive load reported by SDMs exposed to varying types of decision support interventions. Thus, the purpose of this study was to compare the differences in cognitive load reported by SDMs of the critically ill exposed to two different decision support interventions, while controlling for their age.

2. Methods

2.1. Design

This study was a cross-sectional analysis of data generated from a longitudinal randomized controlled trial. The parent study from which the data were generated is ongoing. The primary purpose of the parent study is to evaluate whether two electronic decision aids meet the informational needs of SDMs within the ICU (NIH, NINR R01NR017570). To ensure balance among the study arms, participants were assigned using a minimization procedure based on their gender, race, and relationship to the patient. Prior to data collection (December 2016–March 2018), institutional review board approval was obtained.

2.1.1. Decision support interventions

Participants were exposed to one of two decision support interventions. Specifically, the decision support interventions were electronic decision aids delivered on a 10-inch tablet device, designed to provide informational support for SDMs making decisions for a critically ill loved one. The first electronic decision aid, Information Support (IS), was a 5-minute YouTube video that featured a narrator discussing strategies that family members could use when communicating with a loved one's clinician (Home Instead Inc., 2010). Specifically, the IS video referred to strategies that focused on ensuring conversation concordance between family members and clinicians, advocating for loved ones who may be unable to advocate for themselves, and alternatives to consider when family members felt like their loved ones were not being cared for properly. The IS visual content mainly consisted of video clips of interactions between patients, family members, and clinicians with the narrator's voice superimposed as accompanying audio (Fig. 1). IS was intended to represent a passive learning experience.

The second electronic decision aid, Interactive Virtual Decision Support for End-of-Life and Palliative Care (INVOLVE), was an electronic, avatar-based decision aid designed specifically for the purposes of the parent grant. INVOLVE consisted of two main experiences lasting approximately 7 min. First, a decision coach led the family member to a family conference. Once in the conference room, the decision coach taught the SDM the SBAR3 communication strategy (Clochesy, Dolansky, Hickman, & Gittner, 2015). SBAR3 is designed to enhance communication by encouraging family members to share the patient's story (S), provide information about the patient's background (B) (i.e., pre-admission quality of life and care preferences), ask clinicians for what they need (A), review the clinician's recommendations for the plan of care (R1), consider whether the plan is right for the patient (R2), and repeat the plan of care back to ensure concordance (R3). After the avatar decision coach taught the SBAR3 strategy to the SDM user, the SDM was led to a virtual patient room where a critical care team was waiting to discuss the plan of care (Fig. 2). The SDM was instructed by the decision coach to use all of the SBAR3 components in the conversation with the critical care team. Once in the patient's room, an avatar physician discussed the plan of care of a fabricated patient scenario with the SDM, who was prompted to select preconstructed responses that demonstrated understanding and ability to apply the SBAR3 strategy. Once the conversation with the critical care team ended, the decision coach informed the SDM user if he had successfully incorporated all of the components of the SBAR3 strategy. Unlike IS, INVOLVE was designed to evoke an active user experience.

2.2. Sample

Convenience sampling was used to recruit 97 SDMs from four different ICUs at a tertiary medical center in Northeast Ohio. Two sets of eligibility criteria were used. First, patients were deemed eligible for inclusion if they required at least 72 consecutive hours of mechanical ventilation, lacked capacity to make healthcare decisions, possessed a designated SDM, and were expected to require ICU care for at least two more days. SDMs of eligible patients were approached for enrollment if they were at least 18 years old, able to read and understand English, and able to hear and visualize the content of the electronic decision aids that were delivered on a 10-inch tablet device.

2.3. Measures

2.3.1. Cognitive load

Cognitive load was measured using Leppink and van den Heuvel's (2015) eight-item cognitive load scale (CLS). The CLS has two four-item subscales measuring intrinsic and extraneous cognitive load. The scale's items are measured with an 11-point Likert scale that ranges from 0 (not at all the case) to 10 (completely the case). Each subscale's total score is averaged, with higher scores indicating more cognitive load. Pignatiello et al. (2018) provide evidence of the CLS's discriminant validity with emotion regulation and decision- making preparation and internal consistency (α = 0.89 and 0.75 for the intrinsic and extraneous subscales, respectively). In this sample, the intrinsic and extraneous subscales of the CLS demonstrated acceptable internal consistency (α = 0.90 and 0.81, respectively).

2.3.2. Covariates and demographic characteristics

The covariate, age, and other participant demographic characteristics were obtained using a form created by the principal investigator of the parent study. For the participants, data on age, gender, race, relationship to patient, and education level were collected. Patient demographics (age, gender, and ICU length of stay) were collected through a similar investigator-derived form.

Fig. 1. Example screenshot of visual display for IS.

Fig. 2. Screenshot of interaction with critical care clinician in INVOLVE.

2.4. Procedures

After obtaining written informed consent, a research assistant led the participant to a private location where baseline data of the parent grant could be collected with minimal interruption. These data were collected using face-to-face interviews lasting approximately 30 min. After collection of demographics and baseline data, participants were randomly assigned to a study condition (IS or INVOLVE) by a minimization algorithm. The intervention was restarted if its delivery was interrupted for more than 10 min; this procedure was devised to ensure uniform delivery of the decision aids among the study participants. Immediately after full delivery of the electronic decision aid, the CLS was administered.

2.5. Analysis

SPSS Version 24.0 was used to complete the statistical analyses for this study. Descriptive statistics were used to characterize the sample characteristics and study variables. Next, two analysis of covariance (ANCOVA) models were constructed. In each model, the electronic decision aid (i.e., IS and INVOLVE) was inserted as the independent variable, and age was inserted as the covariate. Intrinsic and extraneous cognitive load were the dependent variables in the respective models. No violations of test assumptions (i.e., linearity, absence of outliers, homogeneity of variance, independent of covariate and treatment effect, and homogeneity of regression slopes) were observed. A priori statistical significance was determined using an alpha level of 0.05.

Table 1
Characteristics of SDMs organized by electronic decision aid (N = 97).

Variables	IS *n* (%)	INVOLVE *n* (%)
Gender		
Female	34 (72)	36 (72)
Male	13 (28)	14 (28)
Race/ethnicity		
White	36 (77)	37 (74)
Non-White	11 (23)	13 (26)
Relationship to patient		
Spouse	19 (40)	19 (38)
Adult child	13 (28)	19 (38)
Sibling	7 (15)	5 (10)
Power of attorney	3 (6)	3 (6)
Other	7 (11)	4 (8)
Education		
High school or less	20 (43)	11 (22)
1–4 years of college	23 (49)	26 (52)
Graduate studies	4 (8)	13 (26)

3. Results

3.1. SDM and patient characteristics

Demographic characteristics of SDMs (Table 1) in this study were similar to other studies with SDMs of the critically ill (Daly et al., 2010; White et al., 2018). Mean age of SDMs in the IS group was 56 years (SD = 13.1), and 52 years (SD = 13.54) for those in the INVOLVE group. Of the 97 total participants, 50 were allocated to the INVOLVE group. The majority of patients were White (75%) and men (53%), and resided in the ICU for an average of 14 days (SD = 8.7).

3.2. Cognitive load levels of the two electronic decision aids

Mean levels of intrinsic cognitive and extraneous cognitive load among participants in the IS group (M = 2.00 and 0.43, respectively) were lower than those in the INVOLVE group (M = 2.60 and 1.32, respectively. To address the aims, two independent ANCOVAs were conducted to identify if there were differences in intrinsic and extraneous cognitive load. The first one-way ANCOVA (F (2, 94) = 4.09, p = .020) (Table 2) indicated that while controlling for age, mean levels of intrinsic cognitive load were not significantly different from one another (F (1, 94) = 2.24, p = .14). The second one-way ANCOVA (F (2, 94) = 9.27, p < .001) (Table 3) indicated that while controlling for age, mean levels of extraneous cognitive load were significantly different from one another between the two study groups (F (1, 94) = 12.11, p = .001). Notably, age was a significant determinant of

Table 2
Summary of ANCOVA with electronic decision aid as independent variable and intrinsic cognitive load as dependent variable while controlling for age.

Variable	Sum of squares	*df*	*F*	*p*	Partial eta squared
Age	45.47	1	6.89	0.010	0.07[a]
Electronic decision aid (0 = IS; 1 = INVOLVE)	14.75	1	2.24	0.138	0.02

Note. F (2, 94) = 4.09, p = .020; R^2 = 0.08.
[a] Power = 0.74.

Table 3
Summary of ANCOVA with electronic decision aid as independent variable and extraneous cognitive load as dependent variable while controlling for age.

Variable	Sum of squares	*df*	*F*	*p*	Partial eta squared
Age	18.12	1	9.05	0.003	0.09[a]
Electronic decision aid (0 = IS; 1 = INVOLVE)	24.25	1	12.11	0.001	0.11[b]

Note. F (2, 94) = 18.56, $p < .001$; R^2 = 0.16.
[a] Observed power = 0.84.
[b] Observed power = 0.93.

intrinsic (F (1, 94) = 6.89, p = .01) and extraneous (F (1, 94) = 9.05, p = .003) cognitive load.

4. Discussion

Our findings indicate that an avatar-based, electronic decision aid (i.e., INVOLVE) was associated with significantly higher levels of extraneous cognitive load compared to a video-based electronic decision aid (i.e., IS). Similarly, intrinsic cognitive load generated by INVOLVE was higher than IS; however, this effect was not statistically significant while controlling for age.

The distinction between intrinsic and extraneous cognitive load is relevant to our findings. Intrinsic cognitive load is determined by the complexity of the presented material and the number of elements that must be processed for learning (Sweller, 2010). The decision aids, IS and INVOLVE, contained similar information (i.e., how to communicate with healthcare providers), which could explain why the intrinsic cognitive load of IS and INVOLVE participants were similar. However, it is possible that the multiple instructional elements within INVOLVE (e.g., the application of a communication strategy to a simulated conversation with critical care clinicians) could elicit a greater degree of intrinsic cognitive load.

Understanding the differences in extraneous cognitive load may be understood in light of prior work (Sweller, 2010). Participants exposed to INVOLVE were likely to exert more cognitive effort to process the additional elements necessary to complete the INVOLVE module relative to participants in the IS condition. For example, INVOLVE recipients were taught a communication strategy and instructed to apply the strategy in a simulated conversation. Thus, extraneous cognitive load may have been elicited through interacting with the INVOLVE interface, understanding the conversational content, or simply understanding how to apply the learning strategy taught by the decision coach. Either way, the elements needing processing did not directly relate to learning the communication strategy; therefore, extraneous cognitive load may have increased (Sweller, 2010).

The differences in extraneous cognitive load between IS and INVOLVE may also be understood in the context of previous empirical research. Chen and Wu (2015), and Homer, Plass, and Blake (2008) found that implementation of additional activity elements increased cognitive load. Similarly, the use of interactive 3D displays also increases cognitive load (Van Der Land, Schouten, Feldberg, Van Den Hooff, & Huysman, 2013). INVOLVE, which incorporated a 3D interface, had a higher amount of elements that needed to be processed to navigate the resource. For example, INVOLVE users were required interact with avatar clinicians by selecting a single response from a list of possible response options. This extra element, which was not necessary for learning, may have increased extraneous cognitive load. However, unlike the present study, Chen and Wu (2015), Homer et al. (2008), and Van Der Land et al. (2013) used proxy measures or single-item indicators of cognitive load, instead of measuring cognitive load's distinct dimensions (i.e., intrinsic and extraneous).

While comparable to the levels of intrinsic and extraneous cognitive load reported in other samples, self-report measurement of intrinsic and extraneous cognitive load is limited to academic or procedural training (Klepsch, Schmitz, & Seufert, 2017; Leppink et al., 2014; Sewell, Boscardin, Young, ten Cate, & O'sullivan, 2016). Our reported findings further supplement the cognitive load literature, as our study is the first to report and compare the intrinsic and extraneous cognitive load levels from technology-based decision aids. Moreover, our findings are unique because of the setting in which cognitive load was measured. To our knowledge, this is the first study to compare cognitive load levels among SDMs within the ICU. The majority of SDMs report profound stress associated with their exposure to the ICU environment (Iverson et al., 2014). Psychological and neuroscientific evidence reports that acute stress may compromise working memory function (Porcelli et al., 2008). Thus, that if INVOLVE and IS were delivered outside the confines of the ICU, different levels of cognitive load may have been reported. Nonetheless, our findings may guide future studies measuring cognitive load from decision aids in other healthcare environments that provoke acute stress. To this point, it may also be worthwhile to consider how varying learning environments influence cognitive load, as updated cognitive load frameworks have been developed that account for environmental factors (Choi, van Merriënboer, & Paas, 2014).

Furthermore, there are theoretical implications from our study findings that may guide future research. In our study, INVOLVE, an avatar-based electronic decision aid, imposed higher extraneous cognitive load than IS, a video-based electronic decision aid. Cognitive load theory states that extraneous cognitive load should be reduced to conserve working memory resources for elements necessary to learn the presented material (Leppink & van den Heuvel, 2015; Sweller, 2010). However, the distinct components of cognitive load are theoretically additive (Kalyuga, 2011; Leppink, 2017). Effective learning is dependent on a balance between the levels of intrinsic and extraneous cognitive load. Therefore, the increased levels of extraneous cognitive load may not be detrimental to learning if the intrinsic cognitive load of the material is not high. Cognitive load theory is currently too insufficiently underdeveloped to ascertain the levels at which intrinsic, extraneous, and total cognitive load levels are detrimental to learning. Thus, future research is needed to elicit the influence of specific cognitive load levels on learning.

There are also practical implications that can be inferred from our findings. While our study suggests that avatar-based decision aids impose a greater amount of extraneous cognitive load, use of avatar-based technology is associated with positive health outcomes among individuals managing a chronic disease or psychological illness (Hickman Jr, Clochesy, Pinto, Burant, & Pignatiello, 2015; Pinto, Hickman Jr., Clochesy, & Buchner, 2013). Furthermore, cognitive load may combat negative physical and emotional feelings (Maranges, Schmeichel, & Baumeister, 2017). Physical and emotional distress is common among SDMs of the critically ill, as well as the 50% of Americans managing a chronic illness (Liddy, Blazkho, & Mill, 2014; Ryan & Sawin, 2009; Wendler & Rid, 2011). Therefore, use of avatar-based technology may provide a means for such individuals to escape their physical and psychological distress without compromising their health outcomes. Cognitive load theory may be further advanced by determining which levels of cognitive load mitigate feelings of physical and psychological distress without unduly compromising working memory such that

information processing and learning is compromised.

Our study possessed several limitations. First, cognitive load was only measured after participants received their intended dose of the electronic decision aid. van Gog, Kirschner, Kester, and Paas (2012) report that cognitive load is dependent on when it is measured; therefore, the internal validity of our study may have been improved if cognitive load was computed by averaging cognitive load scores taken at multiple points throughout the delivery of the electronic decision aid. Furthermore, apart from age, this study did not control for other relevant confounders that may have theoretically influenced cognitive load, such as comfort with technology and education level. Finally, our study was mainly composed of White women serving as SDMs for a critically ill loved one, which limits our ability to generalize our findings.

5. Conclusion

Overall, our results contribute to the development of cognitive load theory. We found that avatar-based, electronic decision aids impose higher levels of extraneous cognitive load than video-based, electronic decision aids. Prior empirical evidence suggests that cognitive load is a determinant of effective learning (Leppink, 2017). Thus, cognitive load may also determine if electronic decision aids meet the informational needs of SDMs for the critically ill. Meeting SDM informational needs is an essential component for them to make informed healthcare decisions for their critically ill loved one. Further research is needed to determine if cognitive load in fact influences the decision-making behaviors and outcomes among SDMs. This line of thinking can be extended to other healthcare domains: i.e., if cognitive load is optimized, it may be possible to optimize healthcare behaviors in other populations where information delivery is an essential component of behavioral change.

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