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The Role of Engagement in Effective, Digital Prevention Interventions: the Function of Engagement in the REAL Media Substance Use Prevention Curriculum

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Abstract

Prevention curricula rely on audience engagement to effectively communicate their messages. However, to date, measurement of engagement has primarily focused on self-report that is often an indicator of liking or satisfaction. Emerging technologies for intervention delivery hold promise not only for additional engagement indicators but also for dissemination outside of traditional vehicles such as classroom delivery. The present study, grounded in the theory of active involvement (Greene 2013), explores the role of engagement (as measured by self-report, program analytics, and observation) with short-term substance use prevention outcomes such as self-efficacy to counter-argue and descriptive and injunctive norms. The study tracks 4-H youth ($N = 310$) engaged with a media literacy focused e-learning substance prevention curriculum, REAL media. Results indicate that self-reports of engagement predicted self-efficacy to counter-argue, but a program-analytic indicator of dosage predicted lower injunctive and descriptive norms, all at 3 months. The observational indicator was correlated with self-efficacy to counter-argue but not significant in the predictive models. The implications and directions for future research regarding how engagement is measured in prevention and included in studying program effects are discussed. Clinical trial: NCT03157700, May 2017.

Keywords Engagement · E-learning · Health messages · Substance use · Media literacy · Involvement · Prevention

Even the most brilliantly designed and executed curriculum is worth little if the audience does not engage with it. This is particularly true for emerging online prevention curricula that exploit connections with digitally immersed youth (Muench 2014; Pradhan et al. 2019), parallel to increasing instructional innovations that use digital technology to deliver a range of content (Henrie et al. 2015). Curricula may sit unattended with little engagement if they do not meet audience needs. Thus, engagement is a central construct in designing and evaluating digital messages (e.g., Dusenbury et al. 2005; Davis et al. 2018; Li et al. 2020; Tobler et al. 2000). One key issue for digital prevention is to identify and understand the role of engagement in the uptake and adoption of healthy practices (Greene et al. 2015; Ma and Lee 2018). Engagement is expected to influence proximal intervention targets by illuminating active program components, ultimately leading youth to decrease drug use or maintain and reinforce nonuse.

Engagement is particularly salient when we conceptualize participants in prevention interventions as active recipients (Arnett 1992; Pettigrew and Hecht 2015). If fidelity in implementation is the primary concern, then audiences may be viewed as passively receiving content. However, emerging theoretical frameworks point to the audience's perceptions of program content as central to prevention intervention effects (e.g., Appleton et al. 2008; Durlak et al. 2010; Greene 2013; Pettigrew and Hecht 2015). In this view, participants are decision makers, actively involved in creating their own pedagogical experiences (Appleton et al. 2008), and the audience "co-creates" the experience with the intervention designer (Pettigrew and Hecht 2015; Pettigrew et al. 2015). We know that student classroom engagement affects school-based intervention program success (Hansen et al. 2019), with interactive programs more successful than didactic ones (see Berkel et al.

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2011; Tobler et al. 2000). This more active view is especially relevant for digital interventions where there is no possibility for a self-correcting implementation process based on user feedback, such as changing style middelivery to make it more engaging. Consistent with this reasoning, active engagement and not participation per se can better explain and predict individual variation in program effects. A central question for prevention interventions is to identify not only overall effects but also for which users the interventions work best (Patrick et al. 2016).

Substance abuse prevention is one of the health promotion areas in which digital universal prevention intervention to delay or prevent substance use onset is most promising (Marsch and Borodovsky 2016; Muench 2014). This is especially relevant given the limitations of time available for school-based interventions and this generation's immersion in digital culture. This move online, however, requires effective evaluation, and evaluation of digital health technologies lags behind technology development (Henrie et al. 2015). This paper examines varying approaches to and effects of measuring engagement with an online prevention intervention.

Engagement in Prevention Interventions

Better understanding prevention program engagement and its relationship with health outcomes is vitally important to advancing digital prevention science, especially focusing on the role of engagement in theories of change or logic models. The term engagement is utilized differently across disciplines (Appleton et al. 2008; Henrie et al. 2015) and is best conceptualized as a multidimensional construct (Appleton et al. 2006) or a metaconstruct (Henrie et al. 2015). For instance, it could include behavioral, emotional/affective, and cognitive components (Fredricks and McColskey 2012; Fredricks et al. 2004). Appleton et al. (2008) note great variability in their review of engagement operationalizations, labels, and definitions. Greene et al. (2015) present a model with four theoretically derived engagement components (personal involvement, perceived novelty, critical thinking, and personal reflection) and measurement. Berkel et al. (2011) identified participant responsiveness with four component indicators (attendance, active participation, home practice, and satisfaction). Clearly, the concept is multifaceted yet not always treated as such, with some data drawn from retrospective item selection in surveys, failing to theoretically inform subtypes (Appleton et al. 2006) and creating challenges to compare across studies (Fredricks and McColskey 2012).

Engagement research in prevention, to date, has focused largely on interventions delivered face-to-face, increasing the urgency to examine this construct in the burgeoning health information technology arena (Pradhan et al. 2019). Program development grounded in user centered design (UCD) and participatory design (PD) is intended to engage the end user in program design (Dopp et al. 2019; Hochheiser and Lazar 2007) and address universal usability (Lyon and Bruns 2019), but these principles have not been consistently applied to measuring program engagement.

Engagement Measurement

Engagement is particularly challenging to measure (Hansen et al. 2019). It can be measured using a variety of methods, but emergence of computer-generated data has been rapid and shifted theory, measurement, and analyses (Henrie et al. 2015). Digital delivery adds the option of program analytics that may provide massive quantities of log data such as time in program or intervention, number of logins, paths or routes taken, clicks, etc.

Much of the prior classroom-based research has been face-to-face (Hansen et al. 2019), with most technology engagement measures reviewed relying on a single data source (Henrie et al. 2015). Henrie et al.'s (2015) review identified more than a dozen varied measures of technology engagement that range from several items to complex factor structures that are theoretically derived and empirically confirmed (see Appleton et al. 2006; Fredricks and McColskey 2012). Like most evaluations of face-to-face delivery, engagement is often measured through self-report (teacher and/or student), at times supplemented by observational approaches in larger funded studies. The field has utilized teacher self-ratings, observations of class instruction (live and recorded, whole and selected portions of lessons), and student reports of engagement. When digital programs emerge, teacher ratings as well as observations of engagement are not applicable in the same way, but program analytics and analyses of responses emerge as potential indicators of engagement because digital platforms can capture program analytic or observation indicators by leveraging log data.

We explore engagement in the present study using three different methods that tap behavioral, cognitive, and emotional forms of engagement (Fredricks et al. 2004): self-report, observational, and program analytic data related to the program. To date, no known studies exist utilizing these three different data sources in the evaluation of adolescent substance use prevention interventions.

Self-Report Measurement

Self-report instruments asking respondents to rate or describe their own thoughts, feeling, or behaviors, have been used in prior engagement studies (see Fredricks and McColskey 2012; Henrie et al. 2015) and provide participants' perspectives but may not capture the behavioral aspects of engagement. They are potentially problematic for prevention due to social desirability bias (Lillehoj et al. 2004; Low et al. 2014).

Many available measures have also been tested primarily with college students, limiting generalizability for middle adolescence. An additional critique is that these studies also often delay evaluation of the program or curriculum, for example assessing programs at the end of the semester and entire courses, limiting analysis of program components and confounding recall rather than immediate perceptions.

Observation Measurement

Observation complements self-report and avoids social desirability issues by third-party examination or coding of participant behaviors but may be labor intensive and costly, limiting widespread utility beyond funded research. Observational measures have been regularly utilized in program fidelity studies where implementers are recorded/coded (e.g., Gottfredson et al. 2010; Pettigrew et al. 2015), but other types of observation variables for prevention are limited to date and provide added potential measures to tap engagement.

Program Analytics Measurement

Analytics provide a third approach emerging out of the interdisciplinary field of digital technology. Interventions delivered through e-learning platforms, websites, and online learning management systems (LMS) offer new opportunities for measuring prevention program engagement by digitally collecting information about how a program is used, an area we label program analytics. For example, programs can collect activity data such as time spent on task, accurate recall, or correct application of program content. Program engagement has been operationalized as time spent on a page/program, eyes on screen, attendance/completion, and correct responses. These operationalizations assess a combination of behavioral and cognitive engagement features, often not clearly articulated. These user interactions and behavior can provide new insights into learning and involvement (Macfadyen and Dawson 2012) as well as other variables such as youth achievement (e.g., Morris et al. 2005; Peled and Rashty 1999). Analytics provide objective data to measure engagement behaviors but may not fully capture the emotional or cognitive elements (see Fredricks and McColskey 2012). Additionally, analytic data may require interpretation of behavior; for example, time spent in a program could indicate deep engagement with program content, someone who is multitasking and not attending to the program, or even perhaps someone who has difficulty navigating the program due to technology or language comprehension challenges.

The current study leverages multiple sources of data (self-report, observation, and program analytics) to tap multiple components of engagement (behavioral, cognitive, and emotional; Fredricks et al. 2004) in response to an online adolescent substance prevention program, REAL media.

REAL Media Program

REAL media is a web-based digital intervention that has demonstrated promise in addressing youth substance prevention (Greene et al. 2016, 2020; Ray et al. 2019). REAL media is adapted from an evidence-based media literacy intervention designed for face-to-face delivery, Youth Message Development (Banerjee and Greene 2007; Banerjee et al. 2015; Greene et al. 2015). It is based on the theory of active involvement (TAI) (Greene 2013; Greene and Hecht, 2013) that articulates the role of engagement in the behavior change process. Using an active involvement approach (Greene and Hecht 2013), TAI describes how engagement with information processing affects immediate outcomes, with the model indicating subsequent effects on cognitive and behavioral outcomes. These REAL media activating intervention features include practice with perspective taking, identifying others' viewpoints, and planning messages as active in initiating change processes. The program teaches youth to critique media advertising content, including analyzing messages promoting substance use; after this foundation, participants then plan, produce, and disseminate their substance prevention messages.

The REAL media program was iteratively developed by target participants in focus groups, interviews, pilot testing, and usability tests across several years (see Greene et al. 2016, 2020; Ray et al. 2019, 2020). The resulting five level self-paced online curriculum is designed to increase self-efficacy to counter-argue (confidence in ability to identify viewpoints that oppose your main argument or are missing) and decrease adolescent substance use/maintain nonuse. It is designed to be highly interactive, using "drag and drop," multiple choice, sliders, fill-in the blank, hover and reveal, and other engaging features that require users to make decisions or participate further in the program. In addition, each level has at least one "optional depth" feature which allows motivated participants to explore a topic in greater detail, as well as a final "challenge" that tests knowledge of key program constructs. In the final level, youth plan, produce and share a counter-message (i.e., substance prevention message) targeting peers. Youth then submit their counter-message to an online social media contest and recruit peers to view/vote for their message.

Hypothesis

The present study utilizes three approaches to measuring engagement and examines their role as predictors of proximal program outcomes. The relationship between and among these approaches is unclear, beyond examining their predictive value. Some studies suggest a weak or negative correlation between analytics such as time spent on tasks and self-reported engagement or learning (e.g., Wagner et al. 2008;

Wellman and Marcinkiewicz 2004). A small pilot study of REAL media reported positive correlations between self-report measures and some program analytic indicators, and generally nonsignificant correlations between self-report measures and observational indicators (Ray et al. 2020). However, the sample was small, and results need to be interpreted with caution. Nonetheless, if the active view of participants and the propositions of TAI are correct, engagement, however measured, should mediate proximal outcomes. Based on the preceding rationale, we hypothesize that program analytics and observational engagement indicators will be positively associated with program outcomes, above and beyond self-report indicators.

Method

Procedure and Participants

Total 639 4-H youth members from nine states across the continental U.S. participated in evaluation of the REAL media intervention using a randomized controlled trial in 2018–2019. Recruitment occurred through two processes: (1) Project staff presented recruitment packages to county leaders, club leaders, and at state events using multiple methods (e.g., video conference, in-person, project website). Club leaders then described the program to club youth; (2) Staff and state level 4-H contacts reached out directly to youth who attended state events or viewed project advertising (e.g., Facebook page, flyers) and contacted the project manager. Parental consent was obtained via email, mail, or text. We provided individual survey links (with youth assent) to participants through email or text. Self-reported assessments were collected at baseline (T1), immediately after intervention (T2), 3-month follow-up (T3), and 9-month follow-up (time 4). All procedures were approved by a university Institutional Review Board, with a DSMB in place to review procedures. Retention rates over three assessments were 74%, 81%, and 78%. Only T1, T2, and T3 data were utilized in the present study (see Consort diagram).

Because we were interested in engagement, we utilized data from youth in treatment only ($N = 349$). Youth who never logged into the intervention ($n = 39$) also were excluded because they could not report engagement with content they had not utilized. Thus, we included a total of 310 youth (198 female and 112 male) who, at the very least, logged into the program (i.e., including those who did not finish any segment) with average age of 14.7 years (SD = 1.33, range = 12–17). Of them, 20 participants (6.5%) reported themselves to be Hispanic; the majority of youth described themselves as White ($n = 273$, 88.3%), followed by Black or African American ($n = 12$, 3.9%), other or mixed race ($n = 10$, 3.2%), Asian ($n = 9$, 2.9%), and American Indian/Alaska Native ($n = 5$, 1.6%). Most of them reported attending public high school ($n = 203$, 65.5%) and almost all participants ($n = 306$, 98.7%) reported access to a computer or tablet at home. They lived across a range of settings including urban ($n = 27$), suburban ($n = 73$), small city ($n = 29$), small town ($n = 98$), and rural ($n = 82$). Participants reported if they qualified for free or reduced cost lunch at school: no ($n = 243$) and yes ($n = 67$), an imprecise SES proxy indicator.

Measures

As participants progressed through the REAL media program, program analytics captured interactions in the levels, including participation in optional content, answers to closed- and open-ended questions, and whether they completed the level. Responses to the open-ended questions comprised the data for the observational measures. Upon completion of the program, respondents completed self-report engagement measures (T2).

Self-Reported Engagement Measures (T2)

Two self-report measures of engagement were used. First, we used 12 items from the 16-item audience engagement scale (AES; Greene et al. 2015). The AES is a multidimensional construct consisting of 4 theoretically derived subscales. Perceived novelty assesses how youth perceive the newness or originality of curriculum (e.g., “This program was different from regular school classes”). Personal reflection taps the degree to which youth perceive what they learned from the curriculum is personally relevant (e.g., “This program made me think a lot about my substance use (drugs, alcohol, tobacco)”). Critical thinking is how youth perceive that the curriculum encouraged them to analyze and evaluate media messages (e.g., “This program made me think about the truthfulness of ad claims”). Involvement assesses the perceived degree of program engagement (e.g., “I got very involved in this program”). All responses were captured on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating stronger engagement with the program (after recoding). We also used the 4-item amount of invested mental effort (AIME) scale (Salomon 1984). AIME refers to the degree to which participants report trying to engage with the program (e.g., “The program made me think”). Participants responded on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater effort invested in completing the program.

The AES engagement subconstructs along with AIME were correlated ($r = 0.20$–0.65); furthermore, confirmatory factor analysis provided a single-factor model demonstrating acceptable fit, with all indictors loading onto one latent factor, $\chi^2(5) = 13.78$, $p = 0.02$, CFI = 0.98, TLI = 0.95, RMSEA = 0.84, and SRMR = 0.03. We therefore created a single global self-reported engagement index by averaging 16 items (12 items from the AES and the 4 AIME items), with a higher score indicating greater self-reported engagement ($M = 3.83$, SD = 0.50, $\alpha = 0.86$).

Analytic Engagement Measures

Two analytic indicators of engagement were measured by the program system and selected to provide variation within the behavioral data. Optional depth is a manifestation of choice, a proxy for interest, and dosage is an exposure variable.

Optional depth is a continuous variable measuring participants' choice to explore additional information within the program. Each level of the program contained at least one place where participants could choose to see more about the topic; if they did not indicate that they would like to see more, participants continued to the next topic. Conceptually, the choice to participate in optional/additional content reflects engagement with materials. Disengaged participants do not voluntarily explore optional content; they complete the material/intervention as quickly as possible. The optional depth score consisted the number of segments (each scored 0 or 1, no and yes) that the respondent chose to explore, with a higher score indicating that participants chose to complete more optional segments ($M = 0.96$, $SD = 1.83$, range = 0–8); some youth did not complete all levels, so their scores would be 0 on indicators of optional depth for that uncompleted level.

The second analytic engagement indicator was a typical construct indicator dosage. Dosage was measured by accounting for whether participants completed each of the five intervention levels and submitted a substance prevention message (poster or video) ($M = 3.96$, $SD = 2.18$, range = 0–6). Youth who did not complete level 1 were considered 0 while youth who completed all five levels and submitted a message to the contest were considered a 6 for dosage.

Observed Engagement Measures

The REAL media program uses text boxes to capture responses to open-ended questions throughout the program. Responses that are highly developed indicate effort and attention and of a higher level of engagement. Those who are less engaged are likely to provide short, cursory responses in contrast to the more elaborated ones from engaged participants. Open-ended responses were coded based on an established coding scheme for cognitive complexity (Role Category Questionnaire, RCQ; Crockett 1965). Cognitive complexity (Burleson and Waltman 1988; O'Keefe and Sypher 1981) is a multidimensional construct which operationalizes an individual's depth of involvement at the level of open-ended written responses. Three dimensions were coded: differentiation (the number of constructs a respondent used in evaluating an issue or ad; constructs in each open-ended response were counted, discounting descriptives and modifiers as defined for RCQ); integration (how well the respondent organized and connected constructs in their response); and abstraction (the degree of concreteness versus abstractness in construct description in the response). Higher scores reflect more complex responses or greater engagement with materials. Scores from individual items were averaged to obtain mean scores for differentiation, integration, and abstraction.

Two research assistants were trained based on RCQ guidelines to code eight open-ended questions that appear in REAL media for the three complexity dimensions. At least one open-ended item was coded in each level, and a sample item included a text box based on a user chosen "best" message in level 3: "What counter-argument was used to make this ad to persuade the audience not to smoke pot / drink alcohol / text and drive?" Interrater reliability was calculated by dimension for each item and across all eight scored items, considering adjacent scores as agreement. Average interrater reliability for all dimensions across all items was high (0.91, exceeding 0.80 for each dimension). A senior researcher scored any items where coders' scores differed by more than 1. A mean score was derived for each dimension from scores across all items.

The three complexity components were highly correlated ($r = 0.37$–0.97); thus, including all three would lead to multicollinearity. We chose differentiation to represent complexity because it is the simplest to operationalize. Scoring for all three requires "unitizing" or identifying a unit as a construct or separate idea. Differentiation involves merely counting these units while integration and abstraction require additional coding. Given the near perfect correlation between differentiation and abstraction, the fact that integration was not significantly correlated with outcomes of interest, and because differentiation is the most basic/parsimonious approach, it made sense to use only differentiation as an indicator of observed engagement in subsequent analyses.

Outcome Measures

In order to assess the effects of engagement, several outcomes were measured. Because engagement occurs at the time of the intervention, we did not anticipate effects on long term or delayed behavioral outcomes such as substance use, which typically emerges later in the process. Instead, we anticipated that engagement with the intervention would impact shorter-term cognitive variables that we measured at 3 months, as specified in our theoretical model: self-efficacy to counter-argue, descriptive norms, and injunctive norms. Based on TAI, the program teaches counter-argumentation and participants created their own substance prevention message counter-arguments in level 5; thus, efficacy to counter-argue is expected to be affected immediately. In addition, self-efficacy has been a key mediator of program effects in other studies (e.g., Banerjee et al. 2015; Colquitt et al. 2000; Pössel et al. 2005) and is central to theories that include engagement (e.g., SCT Bandura 1986; TAI Greene 2013). Descriptive and injunctive norms, although not explicitly addressed in the program, are expected to be influenced by having youth target their peers with messages. As part of this process, for example, they consider if peers are currently using substances, implicating descriptive norms, and the program unpacks strategies advertisers use to imply group acceptance or favorable injunctive norms.

Self-Efficacy to Counter-Argue (T1 and T3) Self-efficacy to counter-argue was measured at T1 and T3 using three items developed by Banerjee et al. (2015). Participants reported how confident they were with behaviors such as "come up with their own evidence or facts that argue against the claims used in the ad" using 5-point confidence scales ranging from 1 (not at all) to 5 (completely). We created a composite variable by averaging items, with a higher score indicating more self-efficacy to counter-argue (T1: $\alpha = 0.78$, $M = 3.60$, SD = 0.87; T3: $\alpha = 0.90$, $M = 3.83$, SD = 0.74).

Substance Use Descriptive Norms (T1 and T3) Descriptive norms reflect beliefs about how prevalent substance use is among participants' peers. Participants estimated the percentage (0–100) of people their age who use seven individual substances (cigarettes/chewing tobacco, snuff, dip, snus, or dissolvable tobacco/electronic vapor product/cigars, cigarillos, or little cigars/alcohol/marijuana/other drugs). We created a composite variable by averaging these seven items, with a higher score indicating perceptions of greater peer substance use (T1: $\alpha = 0.89$, $M = 30.63$, SD = 19.30; T3: $\alpha = 0.91$, $M = 29.97$, SD = 19.76).

Substance Use Injunctive Norms (T1 and T3) Injunctive norms tap beliefs about how acceptable substance use is to others. A total of 14 items were used to assess participants' perceptions that people who are important to them view (a) regular and (b) occasional use of each of the same seven substances as acceptable. Responses ranged from 1 (very unacceptable) to 5 (very acceptable). We averaged the 14 items with higher scores indicating greater perceived acceptability of substance use (T1: $\alpha = 0.91$, $M = 1.66$, SD = 0.61; T3: $\alpha = 0.90$, $M = 1.58$, SD = 0.58).

Analytic Plan

Multilevel regression modeling (e.g., PROC Mixed) in SAS 9.4 was used to account for intraclass correlation by state. Because of the longitudinal design, we addressed attrition and nonresponse by using missing data techniques such as multiple imputation modeling (e.g., PROC MI and MIANALYZE). We separately ran models that varied by outcome of interest (e.g., self-efficacy at time 3 included self-efficacy at T1 but not any other outcomes such as injunctive norms at time 1). We also included in models the covariates age, sex, lifetime substance use, cohort, race, and education type. Except for age, these were included as dummy-coded variables. For example, we included a "sex" dummy-coded variable indicating female as 0 and male as 1. We created a lifetime substance use (never = 0 vs used = 1) when youth reported using at least one prior individual substance (of the seven measured).

Results

Table 1 presents zero-order Pearson's correlation estimates among measures of engagement with the REAL media program with program outcomes at time 3 as well as at baseline (T1). Overall, all engagement indicators (self-reported engagement, differentiation, dosage, and optional depth) were positively correlated with one another. Multilevel regression analyses are reported in Table 2, controlling for a number of variables. Self-report and program analytic variables were significantly associated with theorized outcomes. The significant relationships are discussed below.

Engagement and Program Outcomes

Self-reported engagement was positively related with time 3 self-efficacy to counter-argue ($b = 0.20$, SE = 0.10, $\beta = 0.13$, SE = 0.06, $p = 0.04$) (also see time 1 efficacy and race effects) but differentiation, optional depth, and dosage were not significantly related to self-efficacy to counter-argue at time 3. Overall, youth with higher self-reported engagement reported more efficacy to counter-argue in the context of advertisements.

The program analytic indicator dosage (but not optional depth) was related with both descriptive and injunctive norms at time 3, controlling for baseline demographics and outcomes. Youth with higher program dosage were less likely to report that peers find substance use acceptable (i.e., injunctive norms) ($b = -0.04$, SE = 0.02, $\beta = -0.15$, SE = 0.06, $p = 0.01$). Dosage was related with substance descriptive norms ($b = -1.04$, SE = 0.50, $\beta = 0.12$, SE = 0.06, $p = 0.04$) indicating that youth who had participated in more program levels were less likely to perceive that their peers used substances at time 3. These findings are generally consistent with correlation patterns.

The observation indicator, differentiation, was not significant in any of the predictive models. Ultimately, the observation indicator was not predictive of any time 3 outcomes. The overall effect sizes were small across predictive models and small to moderate for correlations.

Table 1 Pearson zero-order correlations among variables of interest

	M (SD)	Different.	Optional depth	Dosage	Self-reported engage.	T1 self-efficacy to c-arg.	T1 Inj. norms	T1 Desc. N	T3 self-eff	T3 Inj. norms	T3 Desc. norms
Differentiation	1.94 (0.81)										
Optional depth	0.96 (1.83)	0.26***									
Dosage	3.96 (2.18)	0.38***	0.29***								
Self-report eng.	3.83 (0.50)	0.22***	0.27***	0.23***							
T1 Self-efficacy to c-a	3.60 (0.87)	0.13*	0.01	0.05	0.08						
T1 Inj. norms	1.66 (0.61)	− 0.01	− 0.02	− 0.07	− 0.06	− 0.03					
T1 Desc. norms	30.63 (19.30)	− 0.02	− 0.07	− 0.12*	0.02	− 0.06	0.04				
T3 Self-efficacy to c-a	3.83 (0.74)	0.13*	0.07	0.07	0.19**	0.51***	− 0.10	0.01			
T3 Inj. norms	1.58 (0.58)	0.06	− 0.10	− 0.17**	− 0.05	− 0.12	0.51***	0.04	− 0.14*		
T3 Desc. norms	29.97 (19.76)	− 0.05	− 0.09	− 0.19**	0.03	− 0.01	0.05	0.75***	− 0.03	0.08	

Discussion

The goal of the study was to compare engagement measures as predictors of short-term outcomes of a digital, substance use prevention intervention. Keeping students engaged is challenging, and we need to evaluate varied engagement measures to determine impact (Henrie et al. 2015) for theoretically grounded digital interventions (Patrick et al. 2016). In the present study, all the engagement constructs were significantly correlated with each other, indicating they are tapping the same underlying variable. However, only self-reported engagement and a program analytic indicator were associated with program outcomes at 3 months.

Self-reported engagement was the only variable that predicted self-efficacy to counter-argue, a key variable in prevention models that include engagement. Consistent with prior

Table 2 Parameter estimates of engagement indicators on short term outcomes (T3)

	T3 Self-efficacy *B*	SE B	*β*	T3 Injunctive norms *B*	SE B	*β*	T3 Descriptive norms *B*	SE B	*β*
Intercept	1.16**								
Sex (male)	0.13								
Other races (reference = white)	0.29*								
Public school (reference: other types of education)	0.06								
Age	0.03								
Lifetime substance use (yes vs no)	0.01								
Cohort dummy1	− 0.16								
Cohort dummy2	0.11								
Cohort dummy3	0.01								
Self-efficacy at baseline (T1)	0.44***	0.06	0.50	–	–		–	–	
Injunctive norms at baseline (T1)	–	–		0.44***	0.06	0.46	–	–	
Descriptive norms at baseline (T1)	–	–		–	–		0.71***	0.05	0.70
Differentiation	0.04	0.06	0.04	0.09	0.05	0.13	− 0.50	1.13	− 0.02
Optional depth sum	0.02	0.02	0.05	− 0.02	0.02	− 0.07	0.02	0.50	0.00
Dosage	− 0.01	0.02	− 0.02	− 0.04*	0.02	− 0.15	− 1.04*	0.50	− 0.12
Self-reported engagement (total)	0.20*	0.10	0.13	− 0.01	0.08	− 0.01	1.20	1.82	0.03

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

school-based prevention work, self-reports of engagement predicted positive program outcomes (see Hansen et al. 2019; Henrie et al. 2015). This is an important proximal outcome because one of the primary goals was to teach youth the skill of counter-arguing. Content and interactive activities in program level 3 emphasize this concept and allow participants opportunities for practice. For example, youth are asked to identify counterarguments to various ATOD and other advertisements, both in multiple choice and open-ended format. Demonstration of this skill is perhaps the most direct indicator of engagement. Engagement is hypothesized to lead participants to exert greater effort with the curriculum, and this finding is consistent with the present study and active involvement interventions overall (Greene and Hecht 2013). The positive association between self-report engagement and another self-report variable that focuses on one's self-efficacy to apply skills from the curriculum is logical. The self-report engagement measures ask youth to report on the extent to which they were reflective, thought critically, were involved in, and invested mental effort into the program. Thus, it is makes sense that youth with higher scores on these questions also had higher scores regarding their own confidence or efficacy in applying the skills in the future.

Dosage, one program analytic construct, was related to both injunctive and descriptive substance use norms, suggesting that youth who demonstrated higher program use later were less likely to believe that their peers found substance use acceptable and were also likely perceive that youth in their age group used fewer substances. This is an important finding given research that norms are predictive of later substance use (e.g., Elek et al. 2006; Hansen et al. 1998). Notably, REAL media content does not directly address norms the same way it does counter-arguing, although the final online level in which participants plan an antisubstance message targeting peers, along with the execution of that message in poster or video format, has implications for both types of norms. Thus, it makes sense that normative perceptions of youth who completed more of the program—e.g., planned and created their poster targeting peer perceptions—were influenced more so than youth who completed less of the program. However, questions remain as to how much of the REAL media program is necessary to lead to these changes, as well as why some students were motivated to complete more than others. In the present study, nearly 2/3 of participants completed the online program levels, but only ~ 1/3 submitted a message to the contest. Slightly more than 1/3 of participants completed 4 or fewer levels meaning they were never exposed to message planning or production which addresses peer use. Thus, voluntarily completing the program (less than 2 h) may be key. Dosage is important because, as we have argued, engaged participants are more likely to utilize an intervention. This is critical because the youth we most want to target, those at future risk for substance use, may be less likely to consume prevention interventions (Arnett 1992). If we can engage youth through the multiple interactive activities, our findings suggest we can facilitate higher levels of participation and positively influence norms.

Optional depth, the other program analytic construct, was not significantly related to short-term program outcomes but was positively correlated with the other engagement indicators. Although capturing the extent to which an individual voluntarily pursues nonrequired program content arguably taps their engagement in the program, results suggest this is not as important when accounting for self-report and dosage variables.

The findings for differentiation, our observation indicator, were not significant with outcomes. We reasoned that highly differentiated open-ended responses, those with greater numbers of individual concepts described, require greater effort that would only be expended by engaged audiences. If participants do not care about the program, why spend the energy or time to construct a highly differentiated answer? It appears, however, that the measure that identified participants with the capacity and motivation to generate highly differentiated answers is unrelated to program outcomes, at least as operationalized in this study. Differentiation was, however, correlated with program analytics (optional depth, dosage) as well as self-reported engagement.

Situating our findings in the larger context of prevention programming is difficult, as few evaluations of similar types of programs have explored self-report, program analytic, and observational indicators as outcomes within the context of the same study (see Ray et al. 2020). Further, implementation of the REAL media program within the youth 4-H organization, where participation was voluntary further complicates the interpretation. For example, much of the prior youth/young adult research that collects program analytics involves required school assignments, thus it is difficult to compare findings for dosage with our voluntary community-connected program.

Implications

The study has important implications for both the measurement of engagement and for how engagement functions in prevention interventions. To date, valid and reliable measurement of engagement has been lacking in some previous studies (see Hansen et al. 2019; Henrie et al. 2015) and relied predominantly if not exclusively on self-report (for an exception see Dusenbury et al. 2010; Pettigrew et al. 2015; Soffer and Nachmias 2018). The present study utilized self-report, observation, and program analytic data to operationalize engagement. One can, of course, argue with the choices we made within each domain, and this requires additional research. The program log data, for example, creates a large data set for program analytics including time and correct responses that were not currently used, and it is also possible in the future to leverage machine learning to examine log data patterns and/or user responses to open ended items.

The present study found that both self-report and program analytic measures predicted short-term program outcomes. Thus, present evidence would argue for use of either of these measurement approaches depending on targets of interest. Analytics requires greater initial expense in programming and is well-suited for online prevention delivery while costs when using self-report measures are likely to be lower for a single implementation but greater over time if repeated measurement is employed. Had we selected other objective engagement indicators, the findings might have been different, and this can be replicated with additional measures in other samples and with varied prevention topics.

The study also has implications for digital prevention interventions. National educational standards recommend that programs cultivate "engagement", yet little guidance exists for how to best engage youth in prevention (Reynolds and Chiu 2016), beyond key questions of how engagement operates to change behaviors (see Fredricks and McColskey 2012). As predicted in the current study, engagement was a factor is determining short-term program outcomes. Given the expectations that self-efficacy and norms will mediate effects on later substance use behaviors, program designers should consider engagement as central to the development process. This does not mean simply adding gimmicks or games to heighten the "fun" aspect but, rather, developing engaging content that builds requisite cognitive and behavioral skills. This approach argues that programs should be developed with the end user instead of merely for them (Pettigrew et al. 2015). Creative programing is, of course, important but relies on content that is, itself, engaging rather than exclusively on implementation through clever devices or novelty. Our iterative REAL media development phases, guided by UCD and PD principles, identified engaging activities such as open-ended items, sliders, hover/reveal, manipulating images, gamifying challenges, and images beyond strong preference for overall choice/options within the program. Others have described this development processes starting with inclusion of the target audience in formative research and curriculum development (e.g., Colby et al. 2013; Greene et al. 2016; Pettigrew and Hecht 2015; Ray et al. 2019), leveraging UCD with goals to improve translation and implementation. These processes involve design thinking and user research but are more often incorporated in usability testing and intervention development. To date and an area for future research, researchers are not blending UCD with implementation science (Dopp et al. 2019) or leveraging participatory design techniques, beyond examining user needs in technical programming (Hochheiser and Lazar 2007).

Limitations and Conclusions

There are several limitations to this study. First, it relies on a sample of 4-H youth with a specific demographic profile (although across nine U.S. states) that included limited variation in both race (88% White) and ethnicity and overrepresented females. Participants may also differ in other important and unknown respects, and the field may overall underestimate user diversity (Lyon and Bruns 2019), especially in engagement. The current sample may not generalize to other types of community organizations or the U.S. population as a whole, as 4-H has specific types of programs and, accordingly, youth members. One issue for any e-learning interventions would be access, a particular concern in some rural parts of the U.S.A. for example. Another sample could contain different variation in access, user familiarity, and media and social use overall, affecting levels of engagement that are central to the current analyses.

The second limitation, like any study without a great deal of directly comparable research, it may be that selections of the specific engagement indicators neglected key constructs. In addition, it may be useful to design measurement of the effects and outcomes that do not rely exclusively on self-report. Third, this paper focused on short-term proximal effects. It is reasonable based on TAI theory to expect that the effects of engagement would be largely on these shorter-term effects, but it would also be useful to explore mediation or moderation effects for longer outcomes going forward. Fourth, the study utilized a limited set of each type of engagement measurement, thus our selections may have truncated effects. Log data are increasing in use but still underreported, and we need additional studies that use data mining algorithms to search patterns (Henrie et al. 2015). Fifth, the unique variance accounted for overall was small for study effects, and it is important to look at the average effect of the intervention overall, yet we need to examine individual differences in effects or what subgroups receive the most (and least) benefit (Patrick et al. 2016). Finally, like most program evaluations, we are missing systematic analyses of which intervention features are most engaging (Lyon and Bruns 2019) and rely on overall ratings although we do have level ratings in a small preliminary usability study (see Ray et al. 2020). One benefit of our current measurement was that our ratings were temporally adjacent to program use and not delayed. This is a consistent limitation for many studies that do not rate separate components of the program (like some researchers include in pilot and usability tests) or for measurement timeframes delayed by months.

In conclusion, these findings support the importance of considering engagement measurement in digital substance use prevention interventions. Technology-based interventions provide the ability to rapidly expand accessibility of evidence-based prevention for youth (Marsch and Borodovsky 2016; Lyon and Bruns 2019), yet evaluation of digital health technologies lags behind technology development (Muench 2014). Digital interventions are well suited for universal prevention (Marsch and Borodovsky 2016; Pradhan et al. 2019), filling critical gaps in prevention. The suitability of such interventions, however, must be considered in the context of variations in digital access across communities and groups. Despite widespread mobile technology adoption in many U.S. groups, considerable variation in speed and data plans must be taken into account to maximize prevention intervention success. The continued rise in alcohol and tobacco use worldwide, combined with dramatic vaping increases among U.S. youth highlight the urgency of such research. Digital interventions are changing ways to theorize about health behavior change, particularly the multiple levels of influence (Hansen et al. 2019). These changes are at the theoretical, measurement, and analytic levels (Patrick et al. 2016). Although current findings may be unique to the intervention, sample, and/or measures used, they add to a growing body of research supporting the centrality of this engagement construct and encourage more sophisticated consideration of program engagement measures moving forward in prevention science. In an area lacking sufficient data and research driven recommendations, additional research on the role and measurement of prevention intervention engagement is critical.

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Compliance with Ethical Standards

Ethics Approval All procedures involving human participants were in accordance with institutional review board ethical standards and with the 1964 Helsinki declaration and its later amendments. IRB protocol approval #15-544Rc (Rutgers University).

Disclosure of Potential Conflicts of Interest Kathryn Greene and Michael Hecht disclose intellectual property interests in the REAL media curriculum.

Informed Consent We obtained written parental consent and online youth assent for all participants.

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