UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

DEVELOPMENT AND INITIAL VALIDATION OF AN INVENTORY OF STATE EPISTEMIC CURIOSITY: DISTINGUISHING THE INTEREST AND DEPRIVATION DIMENSIONS

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE

By

JOSHUA D. RICE
Norman, Oklahoma
2023

DEVELOPMENT AND INITIAL VALIDATION OF AN INVENTORY OF STATE EPISTEMIC CURIOSITY: DISTINGUISHING THE INTEREST AND DEPRIVATION DIMENSIONS

A THESIS APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

BY THE COMMITTEE CONSISTING OF

Dr. Eric Day, Chair

Dr. Lara Mayeux

Dr. Alex Harris-Watson

Contents

List of Tables and Figures

Abstract

The scholarly literature on epistemic curiosity has predominantly taken a trait-based perspective despite theory espousing its importance as a cognitive-motivational state relevant to learning, achievement, and creativity. Therefore, the purpose of the present study was to develop a state-based curiosity inventory for researchers to use to extend theory on self-regulated learning and performance, distinguishing between interest and deprivation dimensions. The interest dimension refers to the anticipated pleasure of new discoveries. The deprivation dimension refers to the desire to reduce uncertainty and close knowledge gaps. I first demonstrated the substantive content validity of new items and items adapted from existing scales, 24 items in total, per Anderson and Gerbing (1991) using a convenience sample of psychology students. Second, I examined the structural and criterion-related validity of scores using a sample of approximately 248 college males tasked with learning a complex computer game per published lab studies on self-regulated learning and complex skill learning (e.g., Hughes et al., 2013; Hardy et al., 2014, 2018, 2023; Jorgensen et al., 2021). Structural validation analyses suggested a four-factor model, with interest and deprivation dimensions bifurcated into cognitive and emotional components, fit the data better than the a priori two-factor model. Discontinuous growth curve modeling controlling for cognitive ability, prior experience, the Big Five personality, and trait curiosity indicated interest-emotion and deprivation-emotion scores accounted for the variance in game performance. Third, I sought to develop short scales balancing the need for internal consistency reliability with predictive validity. My efforts to develop shorter scales identified viable short 3-to-4 item scales for interest-emotion and deprivation-cognition dimensions but more items need to be developed for measuring interest-cognition and deprivation-emotion dimensions. The results are discussed regarding the need for more work developing and validating scales of state epistemic curiosity.

Development and Initial Validation of an Inventory of State Epistemic Curiosity: Distinguishing the Interest and Deprivation Dimensions

Curiosity was originally theorized by Berlyne (1954), who distinguished epistemic curiosity from perceptual curiosity. Whereas perceptual curiosity refers to the more physiological basis of curiosity, epistemic curiosity refers to the desire for information and knowledge. Despite its origins as a cognitive-based motivational state key to learning, the vast majority of the literature has taken a trait-based approach to studying epistemic curiosity. Indeed, scholars have acknowledged the need for state epistemic curiosity scales (Loewenstein, 1994; Markey & Loewenstein, 2014; Wagstaff et al., 2020) given the inherently dynamic nature to both motivation and learning (Hardy et al., 2019). After early conceptualizations and work on developing epistemic scales (Leherissey, 1971; Naylor, 1981), recent advances have identified two defining dimensions of epistemic curiosity: interest and deprivation (Litman, 2008; Litman & Jimerson, 2004; Litman & Spielberger, 2003). Interest refers to the anticipated pleasure of new discoveries, whereas deprivation refers to the desire to reduce uncertainty and close knowledge gaps. However, currently there is not a well-validated state-based measure of epistemic curiosity that includes subscales for both interest and deprivation that are easily adaptable across a wide-range of learning and achievement contexts. Such a measure would be useful toward building theory and developing practical interventions in areas concerning learning, performance, creativity, and perhaps even allaying the adverse effects of anxiety (Loewenstein, 1994). In particular, there is a need for a state-based measure of epistemic curiosity that can be used in longitudinal, repeated-measures research to test and build theory of dynamic phenomena that occur in relatively short periods of time. For instance, such a state-based measure could be useful for extending theory on self-regulated learning.

Therefore, the primary purpose of the present study was to examine initial validation evidence for a new 24-item state-based epistemic curiosity self-report inventory that distinguishes interest and deprivation dimensions. Hereafter, I refer to this inventory as the State Interest and Deprivation Epistemic Curiosity Scales (SIDECS).

In doing so, I took a three-pronged approach. First, I examined the substantive content validity of items per recommendations of Anderson and Gerbing (1991) and Colquitt et al. (2019) using a convenience sample of psychology graduate and undergraduate students tasked to sort items between interest and deprivation dimensions. Second, I examined the structural validity of scores via confirmatory factor analysis, comparing two- and single-factor models as well as a post hoc four-factor model that bifurcated the interest and deprivation dimensions into cognition and emotion facets. Third, I examined the external validity of scores by testing the criterion-related validity and incremental validity of scores, predicting the acquisition and adaptation of skilled performance on a complex and fast-paced videogame used in previous research on self-regulation and complex skill learning (e.g., Hughes et al., 2013; Hardy et al., 2014, 2018, 2023; Jorgensen et al., 2021). For the second and third prongs, I used a sample of 248 undergraduate students from the University of Oklahoma Department of Psychology participant pool. Using a task-change paradigm and discontinuous growth modeling, I compared the extent to which SIDECS dimensions predicted performance beyond general mental ability, past experience, trait-based epistemic curiosity, and Big-Five personality scores.

The secondary purpose of this study was to develop shorter scales that can be used in future research where there is a need for efficient measurement without sacrificing psychometric quality. In particular, I examined item-level information and developed short scales that balanced internal-consistency reliability with predictive validity. I intend to use short scales in future studies that examine the dynamic relationships among epistemic curiosity dimensions and other self-regulation variables (e.g., self-efficacy, metacognition, and task exploration). The following sections will give an account on the theoretical origins of epistemic curiosity and its measurement, the need for a new inventory, a summary of my methodological approach and results, and a discussion of the implications of the results and need for future research.

Theoretical Origins of Epistemic Curiosity

Aristotle once opined “all men by nature desire to know” (Ross, 1924, p. 2). The origins of the study of curiosity within psychology begin with William James theorizing that curiosity is an innate instinct within individuals. This instinct is to understand the cause of something as well as assimilating new information with old information (James et al., 1890). Freud acknowledged that curiosity is analogous to a thirst for knowledge. Gestalt Psychologists emphasized “principles of closures” in taking actions to close a “gap.” Reinforcement theory explained that an organism learns to understand their environment (Berlyne, 1954).

Berlyne (1954) was the first psychologist to put an intentional focus on the study of curiosity. Berlyne (1954) distinguished between perceptual curiosity and informational curiosity. Perceptual curiosity addresses the urge to experience stimuli (Berlyne, 1954). Informational curiosity, more commonly termed “epistemic curiosity,” addresses the desire for knowledge. Akin to more current work on interest- and deprivation-dimensions, Berlyne (1966) also described epistemic curiosity as the key motivator for diversive exploration and specific exploration. Diversive exploration occurs when the environment contains something novel or surprising. Specific exploration arises due to the discomfort in the face of the lack of information or understanding.

Building on this discomfort aspect of curiosity, Lester (1968) described the role that anxiety plays in fluctuations of curiosity. Day (1982) emphasized an optimal zone of curiosity between boredom and anxiety. Spielberger and Starr (2012) drew attention to the motivating effect of anxiety on curiosity.

Loewenstein’s (1994) theory focused on moments when cognition induces a feeling of deprivation in the face of an “information gap”. The information gap perspective serves as a reference between what an individual currently knows and what they could know. The perspective of an information gap also provides further understanding on the environment highlighting those gaps in knowledge through questions, feedback, or when expectations are violated. Loewenstein’s (1994) critical review of the earlier literature showed that there had not been a sufficient focus on why individuals voluntarily expose themselves to the discomforts of curiosity or what the situational determinants for curiosity are. Such situational determinants might be problems, questions, violated expectations, and struggles to recall information. Nevertheless, Loewenstein (1994) acknowledged that it is common for people to seek information simply because it is interesting.

Current Theories of State Epistemic Curiosity

Educational psychologists have studied epistemic curiosity to better understand and facilitate scholarship in students (Fisher, 2000). Markey and Loewenstein (2014) emphasized that the intensity of the arousal of curiosity lies in the importance, salience, and surprise found in material presented to learners. The more important information is to someone, the more curious the individual becomes. Salience refers to how the environment reveals information gaps. An example of salience is when a teacher asks a question to students knowing full well that the students do not fully know the answer. Surprise is the violation of expectations and allows the individual to be open to more curiosity, also discussed by Loewenstein (1994). Peterson (2020) mapped a student's environment via Bioecological Systems Theory to identify what spurs or weakens curiosity.

Epistemic curiosity has also been invoked in research on self-regulated learning in the workplace. For instance, Hardy et al.'s (2019) Dynamic Exploration-Exploitation Learning (DEEL) Model draws parallels to interest and deprivation dimensions in training environments that grant considerable autonomy to learners. DEEL articulates how novelty motives play a role in the motivation to seek out more complexity in a task environment, reflecting interest. DEEL also emphasizes information gaps and uncertainty as a motivating factor for navigating the breadth and depth of knowledge and skill, reflecting deprivation. DEEL illustrates the optimum shifts in the proportion of effort devoted to exploring a task environment versus exploiting what one already knows based on the magnitude of the information-knowledge gap. Exploration is emphasized with larger information-knowledge gaps, whereas exploitation is emphasized when there are smaller gaps. The high uncertainty accompanying large information-knowledge gaps guides learners to develop breadth over depth in learning, akin to the interest dimension (i.e., diversive curiosity). The low uncertainty with small information-knowledge gaps guides learners to address the specific elements of uncertainty, matching the deprivation dimension (i.e., specific curiosity).

The parallels of interest to exploring and deprivation to exploiting sheds light on the findings of Steele et al.'s (2021) study of creativity, showing that exploration is more related to the novelty of solutions whereas exploitation is more related to usefulness. These findings are valuable in the potential explanation of the current relationship between curiosity and creativity. For instance, Hardy et al. (2017) specifically addressed the need to understand how curiosity impacts creative performance via information seeking and idea generation. Individuals with higher trait-interest curiosity that manifested higher creative performance spent more time exploring information. Idea generation also fully mediated the process between the time spent exploring information and creative performance.

Shin and Kim (2019) echo the notion that information-knowledge gaps stimulate curiosity, while disentangling situational interest from curiosity. Situational interest is spurred from a variety of sources of positive affect that may not be due to informational value, whereas epistemic curiosity focuses on the information and the affective components surrounding it specifically. Cognitive equilibrium, a reduction in curiosity, is theorized to occur when the deprivation curiosity is resolved through filling the information-knowledge gap.

Correlates of Epistemic Curiosity

Recent research has examined the extent to which trait curiosity is related yet meaningfully distinct from a variety of other constructs established in the literature. For example, learning goal orientation, need for cognition, and typical intellectual engagement are among the strongest correlates of epistemic curiosity, suggesting redundancy and questions about the discriminant validity of measures of trait curiosity (Mussel, 2013; Mussel, 2010). In this vein, research also shows a strong correlation between interest in a topic and epistemic curiosity (Mussel, 2013). Nevertheless, it has been argued that situational interest and epistemic curiosity are meaningfully distinct with situational interest stemming more from the experience of positive affect whereas curiosity stems more from a desire to learn information. Among the Big Five personality dimensions, openness to experience yields the strongest correlations with epistemic curiosity followed by conscientiousness (Grossnickle, 2016; Mussel, 2013).

With respect to the interest versus deprivation distinction, despite a strong correlation between the two dimensions of epistemic curiosity, they are differentially related to other constructs (Grossnickle, 2016). Whereas interest curiosity is negatively related to unpleasant emotions such as anger, anxiety, and depression, deprivation curiosity is positively related to such emotions (Litman et al., 2010). Interest curiosity is positively correlated with ambiguity tolerance, but the correlation for deprivation curiosity is negative (Litman et al., 2010). With respect to achievement motivation (i.e., goal orientation), higher scores for interest curiosity are associated with higher mastery (i.e., learning) motivation, whereas higher scores for deprivation curiosity are associated with higher performance-approach and performance-avoid motivation (Litman, 2008).

In general, there is a debate among scholars regarding the relative theoretical importance of the interest and deprivation dimensions. Berlyne (1966) and Loewenstein (1994) emphasized the deprivation dimension and its role in the reduction of information gaps, and they downplayed the importance of the interest dimension, suggesting it was more related to entertainment, boredom, and phenomena unrelated to curiosity. Yet, Grossnickle (2016) and Litman (2008) argued for the importance of the interest dimension, saying that information can be sought for enjoyment and pleasure, which can arouse novelty and uncertainty. And as mentioned above, Hardy et al. (2017) showed interest was better linked to information seeking and idea generation in creative performance than deprivation. Similarly, Huck et al. (2020) found interest curiosity better predicted complex skill acquisition and adaptive performance than deprivation curiosity. The reliance on trait-based scales of epistemic curiosity is a key limitation of this empirical literature.

Research using validated state scales would go a long way toward better testing and building theory on how the interest and deprivation dimensions are connected to each other and differentially linked to other constructs. For instance, and in similar respects to Hardy et al.'s (2019) DEEL model, interest curiosity may guide individuals to expand their information gaps while the deprivation dimension could guide individuals to reduce their expanded information gaps. Likewise, reducing an information gap may bring a greater interest for more information. Based on the extant literature, epistemic curiosity is the bridge between awareness of information gaps, emotions experienced in relation to learning and achievement, and choices made for how to approach learning and achievement contexts (e.g., exploration and exploitation). Research with validated state scales could inform interventions for effectively stimulating curiosity with a range of proximal and distal behavioral outcomes in mind, including problem solving, feedback seeking and acceptance, persistence, and academic and workplace learning and achievement (Loewenstein, 1994, Mussel, 2013; Wagstaff, 2020).

Epistemic Curiosity Scale Development

Initial scale development was state-based, then researchers turned to trait-based scales when attempting to identify and distinguish different dimensions with different subscales (see Table 1). State based measures exclusively focused on positive emotions and heightened arousal. Leherissey (1971) developed a state epistemic curiosity scale for academic contexts that asked questions on whether educational material was interesting or exciting. Naylor (1981) created the Melbourne Curiosity Inventory (MCI) to measure states of anticipated pleasure for learning information. Naylor (1981) also showed discriminatory evidence in the factor structure for the difference between state and trait curiosity, suggesting that measuring state epistemic curiosity needs to be measured and understood related to yet apart from trait curiosity. Spielberger and

Starr (as cited by Boyle, 1983) formed the commercialized State-Trait Personality Inventory, with curiosity focusing only on the interest aspect.

Litman and Spielberger (2003) were the first to create a trait measure for epistemic curiosity including the specific and diversive components called the Epistemic Curiosity Scale (ECS). Extending work with the ECS, Litman and Jimerson (2004) reasoned that the motivation behind exploration was due to the pleasurable feelings of interest and aversive feelings of uncertainty. Litman and Spielberger (2003) placed an emphasis on curiosity as an interest (e.g., the ECS specifically) but lacked a deprivation component. Therefore, Litman and Jimerson (2004) created the Curiosity as a Feeling of Deprivation Scale (CFDS) to begin measuring this aversive component to trait epistemic curiosity.

As the ECS and CFDS were developed, differences and similarities between them were examined. The CFDS scores correlated with anxiety, anger, and depression while the ECS scores did not (Litman, 2008). CFDS scores were also more correlated with measures of general epistemic state curiosity, higher information seeking, and different metacognitive knowing states (Litman et al., 2005). Across studies, correlations between the ECS scores and CFDS scores ranged from .68 to .70 (Litman & Jimerson, 2004; Litman & Silvia, 2006), showing convergent validation evidence for the two scales. Litman and Silvia (2006) first established evidence in support of a two-dimensional framework with a confirmatory factor analysis involving both scales. Litman (2008) showed further support for a two-dimensional framework again using both scales via a series of exploratory and confirmatory factor analysis across separate samples. Litman (2008) proposed replacing the terms “diversive” and “specific” with “interest” and “deprivation,” respectively, as the latter terms better reflect the affective aspects to curiosity. It should be noted that often in the literature the interest and deprivation dimensions are referred to as “types.” Despite the importance of Litman’s groundbreaking work (Litman, 2008; Litman & Jimerson, 2004; Litman & Spielberger, 2003) to clarifying the dimensionality of epistemic curiosity, the need for state-based measures remains.

In at least four different reviews of curiosity research, the need for greater scale development and understanding of state epistemic curiosity has been expressed (i.e., Loewenstein, 1994; Markey & Loewenstein, 2014; Wagstaff et al., 2020; Gross et al., 2020). Despite psychometric evaluation of previous scales (see Table 1), the findings of Litman (2008) indicate epistemic curiosity must distinguish interest and deprivation dimensions. Previous state scales (e.g., MCI, Leherissey’s State Epistemic Curiosity Scale, STPI-Curiosity) do not contain distinct interest and deprivation subscales.

Research on epistemic curiosity is limited without capturing trajectories and fluctuations in both interest and deprivations dimensions. Capturing the interest and deprivation dimensions identified by Litman (2008) at the state level will allow researchers to give new insights into previous theory on state epistemic curiosity as described by Berlyne (1954). Measuring interest and deprivations aspects of state epistemic curiosity will allow better prediction and explanation of learning, achievement, and creative outcomes, in particular the interplay between the cognitive, motivational, and emotional processes associated with the acquisition and adaptation of knowledge and skill across a variety of contexts including work, education, and recreational pursuits.

Learning and self-regulation are dynamic processes that occur at the within-person level, which unfold over time with repeated measurement (Hardy et al., 2018). The measurement of epistemic curiosity, learning, and self-regulation variables has predominantly involved between-subjects research designs, whether cross-sectional or lagged (Hardy et al., 2019). It is critical to longitudinally measure and examine the dynamic processes that involve epistemic curiosity to understand phenomena at the within-person level. Examining trajectories and fluctuations in epistemic curiosity would provide rich opportunities to gain insight into information gaps, the impacts of interest and deprivation on one another, and how self-regulation processes unfold over the course of learning, achievement, and creative problem solving. What happens to interest and deprivation dimensions as information gaps are closed or when individuals realize they have new information gaps? Do changes in interest and deprivation curiosity have different impacts on how individuals think about what they have learned and persist in various learning, achievement, and creative contexts? Before such questions can be addressed, scales for both interest and deprivation dimensions are needed. Hence, for the present study I sought to develop and examine the psychometric properties of scales for each dimension in a lab context used in previous research on self-regulated learning and complex skill learning (e.g., Hughes et al., 2013; Hardy et al., 2014, 2018, 2023; Jorgensen et al., 2021) using the computer game Unreal Tournament 2004 (UT2004; Epic Games, 2004).

Method

Initial Scale Development

Trait scales focus on general individual differences (e.g., “Enjoy exploring new ideas”, Litman, 2008, p. 1593), while state scales should refer to the context of a specific activity (Loewenstein, 1994). Naylor (1981) used this method to examine contexts in a math lesson. Accordingly, for the present study, all the items were created in relation to the task at hand (i.e., Unreal Tournament 2004). Items for the SIDECS were adapted from previous scales (see Tables 2 and 3), with one original item written to explicitly emphasize gaps in knowledge, “There are gaps in my understanding of Unreal Tournament that I want to fill” for the deprivation scale.

Trait scale items were adapted to reflect how an individual may feel at a particular moment about a task or activity. The scales of Litman and Spielberger (2003), Litman and Jimerson (2004), and Naylor (1981) have shown predictive validity and many of these items were not included in Litman (2008). The SIDECS contains the Litman (2008) items as well as items from the aforementioned scales. Litman and Jimerson (2004) articulated and found support for three subdimensions of deprivation: problem-solving, intolerance, and competence. At least three items of each of these subdimensions were used in the present scale. Items reflecting interest and deprivation dimensions that were not redundant with other scale items were selected from Naylor's (1981) Melbourne Curiosity Inventory. Many items from Huck et al.'s (2020) adaptation of the trait epistemic curiosity scale by Litman (2008) were used given it involved the same criterion task—Unreal Tournament 2004 (UT2004; Epic Games, 2004)—as in the current study. The initial development resulted in 11 interest dimension items and 13 deprivation dimension items. SIDECS items were written to be easily adaptable across a range of tasks and activities. Appendices A and B show the interest and deprivation scales, respectively across four contexts: UT2004, statistics, Excel, and tennis.

Substantive Content Validation of the Current Scales

I examined the substantive content validity using the sorting method developed by Anderson and Gerbing (1991). The method involved providing definitions of the interest and deprivation dimensions and having respondents sort each item into the dimension they thought was the better fit. The definition provided for the interest dimension was, "Interest involves the anticipated pleasure of new discoveries" (Litman, 2008, p. 1586) and for the deprivation dimension, "Deprivation refers to reducing uncertainty and eliminating undesirable states of ignorance" (Litman, 2008, p. 1586).

I used a convenience sample of 16 graduate and undergraduate students at the University of Oklahoma. All the participants were naïve to the scholarly literature on curiosity. Per Anderson and Gerbing, for each item I calculated substantive agreement scores and substantive-validation coefficients. Substantive agreement (p_{sa}) is calculated as the percentage of respondents who correctly sorted the item into the intended dimension. The substantive-validation coefficient (c_{sv}) is calculated as the number of respondents who correctly sorted the item minus the number of respondents who incorrectly sorted the item, divided by the total number of respondents. Tables 4 and 5 show the results for the interest and deprivation items, respectively. The average scores, p_{sa} = .90 and c_{sv} = .80, indicated that both scales had high substantive content validity. All the c_{sv} scores were at or above the .50 standard suggested by Anderson and Gerbing (1991), indicating every item had evidence of substantive content validity. Despite the supportive evidence, a change was made to the deprivation dimension item “I want to keep learning until I fully understand Unreal Tournament” to provide greater conceptual alignment and coverage to the scale. Specifically, this item was dichotomized into two separate deprivation items “I will keep trying hard until I fully understand Unreal Tournament” and “I feel uncomfortable when I don’t understand something about Unreal Tournament.”

Structural Validation and External Validation

Participants

A lab study involving young adult males from University of Oklahoma’s Department of Psychology participant pool was used to examine the structural validity (i.e., confirmatory factor analysis) and external validity (i.e., criterion-related validity and incremental validity) of SIDECS scores. Participation involved only males given the substantial gender differences in interest, experience, and enjoyment of computer games similar to the criterion task used in this study (Hopp & Fisher, 2017; Hartmannn & Klimmt, 2006). Participants received research credit for participating, and all participants who performed in the top 50% (based on individual trial performance) were entered into a drawing for an additional $25 gift card.

Initial sampling contained 282 participants. Participants were excluded for computer errors (n = 17), missing data (n = 15), flatlining repeatedly on performance measures (n = 1), and failure to follow instructions (n = 1). The final analysis resulted in 248 participants. The age of the participants ranged from 18 to 32 (M = 19.40, SD = 2.03). 154 participants (65.1%) reported their ethnicity as Caucasian, 11 (4.4%) as Black/African American, 23 (9.3%) as Hispanic/Latino, 11 (4.4%) as Native American, 21 (8.5%) as Asian, 20 (8.1%) as multiple (two or more ethnicities), and 3 (1.2%) as other.

Performance Task

The performance task in the present study is Unreal Tournament 2004 (UT2004; Epic Games, 2004), a commercially available first-person shooter computer game that has been used previously in research on self-regulation and complex skill learning (e.g., Hardy et al., 2019; Hardy et al., 2014; Hughes et al., 2013). Unreal Tournament is fast paced, cognitively complex, and requires perceptual motor skills due to using the keyboard and mouse simultaneously. Despite the relative ease in understanding the game elements, mastery of the task itself is difficult. UT2004 is suitable for studying active learning and self-regulation phenomena due to its technology mediated, shifting, ambiguous, and emergent task qualities (Hardy et al., 2019; Keith & Wolff, 2015). UT2004's dynamic and immersive environment reflects demands similar to training and development programs that involve the use of computer games, simulations, and other synthetic learning environments, which have increased in workplace training given the interactive experience they provide learners (Bell et al., 2008; American Society for Training and Development, 2015).

The setting of the game is a science fiction futuristic time with different races, locations, and weapons. The objective of the participant is to control an avatar and destroy enemy opponents without being destroyed themselves in a free-for-all type of match. The participant's avatar and enemy bots reappear in the game when their character is destroyed until the timer runs out. The participant begins each match and after each death with a basic weapon and may acquire other weapons and resources (i.e., pickups). These resources can enhance the participant's health, defense, attack power, special abilities and are consistently placed in selected locations on the map. Each weapon has unique strengths and weaknesses, and it is up to the participant to make decisions on which weapon to use in different circumstances.

Procedure

All participants were told that the purpose of this study was to investigate how different people learn dynamic and complex tasks. Participants sat in individual cubicle rooms each with a computer station. Participants first completed an informed consent form followed by a set of self-report questionnaires including demographics, past videogame experience, trait-based epistemic curiosity, the Big-Five Personality, and several other measures not germane to the study's purposes. Participants were then told that for every trial in which their performance score falls within the top 50% of all performance scores, they will be entered in a drawing to win one of five $25 gift cards.

A 15-min. training video was shown to participants on the controls, weapons, and resources available for UT2004. Participants were then given a 1-min. practice trial with no enemies and a sheet describing the information in the training video. Scratch paper and a pen were provided to participants to record their scores or take notes.

Participants completed 28 trials total at 4-min apiece. A 4-min duration was chosen based on previous research using UT2004 showing variability across participants and a pattern of means reflecting a basic learning curve (e.g., Hughes et al., 2013; Hardy et al., 2014). Session scores consisted of 2 trials being averaged (i.e., 14 sessions total). Averaging trial scores allows performance estimates to be more stable by reducing noise.

Halfway through the protocol an unexpected task change was introduced, thus prompting a need for adaptation in response to increases in task complexity (Hughes et al., 2013). Before the task change, the number of opponents was 2 and the difficulty of the enemies was set to “4” (On a scale from 0-7 with 0 as the easiest and 7 as the most difficult). The first map was a small canyon fortress area with barriers on the perimeter. After the task change, the number of opponents increased to 9 and the difficulty of the enemies increased to “5”. The second map was a darkened platform with multiple levels and freedom to fall with no barriers on the perimeter. The difficulty of “4” and “5” were chosen based on previous studies using UT2004 (e.g., Hughes et al., 2013). The SIDECS inventory was given in between Sessions 7 and 8, thus just prior to the task change. Validation of the SIDECS inventory was not the primary purpose of this data collection, and there was only time in the protocol for one administration. Given this constraint, I chose to administer the SIDECS at this point in the protocol because 14 games of practice would assure between-person variability in scores needed to examine structural and external validation evidence. Participants were debriefed following the final session.

Measures

Task performance. Task performance scores were calculated per the formula used in previous research (e.g., Hardy et al., 2019; Richels et al., 2020): the number of kills (i.e., the number of times that a participant destroyed a computer-controlled bot) divided by the quantity of kills plus player deaths (i.e., the number of times a participant themselves is destroyed), plus player rank (i.e., the participant's rank relative to the bots within the trial). To increase ease of interpretability, performance scores are multiplied by 100. As mentioned above, session scores are the average of each pair of trial scores.

State Interest and Deprivation Epistemic Curiosity Scales. The order of the SIDECS items was randomly determined and standardized (see Tables 2 & 3).

Control variables. General mental ability (GMA) was measured through self-reported scores of the ACT/SAT. Videogame experience was measured the same as in previous studies (Hardy et al., 2019; Richels et al., 2020; Hughes et al., 2013) using four items. The first two items were "Over the last 12 months, how frequently have you typically played video/computer games?" and "Over the last 12 months, how frequently have you typically played first-person?". Participants responded to these items on a 5-point Likert scale (1 = *not at all*, 5 = *daily*). The second two items asked participants how many hours per week they play any type of video/computer game and how often they play specifically first-person shooter video/computer games. Scores for each pair of items were standardized and then averaged into a single composite score. Internal consistency estimates range from .72 to .86 in previous studies (i.e., Richels et al., 2020; Hardy et al., 2014; Hughes et al., 2013). Scores for the Big Five personality variables were measured using Goldberg's 100 Unipolar Markers (Goldberg, 1992) with a Likert scale (1 = *extremely inaccurate*, 9 = *extremely accurate*). Participants rated how well each adjective describes them. Each of the five-personality factors contains 20 items. Richels et al.

(2020) reported coefficient alpha reliability estimates ranging from .75 to .91 across the five scales in a previous lab study with UT2004. Trait interest and deprivation epistemic curiosity were measured using Litman's (2008) 10-item scale with reliability estimates of .75 for interest and .80 for deprivation (Litman & Mussel, 2013). Participants responded to items on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*).

Results

Structural Validation

Confirmatory factor analysis (CFA) involving a comparison of three a priori models was conducted to examine the structural validity of the SIDECS scores: a single-factor, unidimensional model, a two-factor uncorrelated model, and a two-factor correlated model. I expect the two-factor correlated model to provide the best fit per Litman (2008). The factor variances were set to 1.00 with maximum likelihood (ML) as the estimator.

I used several criteria to assess model fit: root mean square error of approximation (RMSEA), standardized root mean residual (SRMR), comparative fit index (CFI), Tucker-Lewis Index (TLI), and χ^2/df were used to examine the absolute fit of the models. For absolute fit values, Schermelleh-Engel et al. (2003) suggest χ^2/df values below 3 indicate acceptable fit and values under 2 as good fit. Sharma et al. (2005) suggests RMSEA values smaller than .08 indicate acceptable model fit with values below .06 indicating good fit. MacCallum et al. (1996) recommends the upper bound of the RMSEA 90% confidence interval be below .10 for acceptable fit. The SRMR values below .10 indicate acceptable fit and values below .05 indicate good model fit (Schermelleh-Engel et al., 2003). CFI and TLI values larger equal to or exceeding .90 indicate acceptable fit and values larger than .95 indicate good model fit. The Akaike information index (AIC) and χ^2 difference tests were used to examine the relative fit of the different models.

As expected, the lower AIC values along with the χ^2 difference tests indicated the two-factor correlated model provided the best fit with the majority of the absolute fit indices for this model suggesting acceptable fit (χ^2/df = 2.40, SRMR = .07, RMSEA = .075, RMSEA upper bound 90% CI = 0.083), while the CFI (.88) and TLI (.87) showed unacceptable fit (See Table 6).

Given these CFI and TLI values, I then decided to pursue a model with better fit based on an examination of the modification indices, item intercorrelations, and the wording of items. From this examination I noticed that items involving emotion words (e.g., enjoy, excites, frustrates, aggravates) within the interest and deprivation scales tended to correlate more with each other than with other items that did not contain emotion words. Consistent with Berlyne's (1954) early conceptualization of how curiosity involves a cognitive search to find answers to questions as well as the emotions that arise from searching for answers, I then bifurcated the interest and deprivation scales into cognitive and emotional facets and examined the fit of a four-factor correlated model: interest-emotion (i.e., items 5, 6, 9, 10, 11, 16, 17, 23), interest-cognition (i.e., items 2, 12, 21), deprivation-emotion (i.e., items 1, 3, 8, 13, 18), and deprivation-cognition (i.e., items 4, 7, 14, 15, 19, 20, 22, 24). Such bifurcation of interest and deprivation curiosity is also consistent with more current theorizing from Litman (2008) who indicated that both dimensions of curiosity include affective components. As shown in Table 6, although the CFI (.89) and TLI (.88) did not reach the acceptable threshold, both the absolute (χ^2/df = 2.26, RMSEA = .071, RMSEA upper bound 90% CI = .079, SRMR = .07, CFI = .89, TLI = .88) and relative fit ($\Delta\chi^2$ = 48.06, Δdf = 5, $p < .05$) were better for the four-factor correlated model compared to the two-factor correlated model. Accordingly, in the analyses for the external validation of the SIDECS I examined scale scores for the four dimensions while controlling for the trait scores using the traditional two dimensions.

External Validation

Table 7 shows the means, standard deviations, and correlations for all the study variables. Correlations between the SIDECS scores across the four dimensions with GMA, videogame experience, and the Big Five were weak (all *r*s < |.18|) and predominantly not statistically significant. Similarly, correlations with trait scores were weak, with statistically significant effects only for trait interest with state interest-emotion ($r = .15$, $p < .05$), trait deprivation with interest-cognition ($r = .16$, $p < .05$), and trait deprivation with deprivation-cognition ($r = .17$, $p < .05$). Correlations among the SIDECS dimensions were all statistically significant, ranging from .36 ($p < .01$) between interest-emotion and deprivation-emotion to .73 ($p < .01$) between interest-emotion and interest-cognition.

With respect to criterion-related validation evidence, correlations with performance for the interest-emotion ($r = .41$, $p < .01$), interest-cognition ($r = .24$, $p < .01$), and deprivation-cognition dimensions ($r = .27$, $p < .01$) were all statistically significant while the correlation for deprivation-emotion was not ($r = 0.00$).

I then used discontinuous growth curve modeling to further examine the criterion-related validity of the SIDECS scores in terms of their incremental validity in predicting skill acquisition (i.e., pre-task change) and adaptation (i.e., post-task change) performance scores. I used the same coding scheme as Richels et al. (2020) per recommendations of Bliese and Lang (2016). Table 8 shows the specific dummy codes. Skill acquisition (SA) refers to the linear change in scores across all sessions. Transition adaptation (TA) models discontinuity, indicating when the task change occurred (i.e., from Session 7 to Session 8), which allows post-change scores to be compared with pre-change scores. Reacquisition adaptation (RA) refers to changes in the linear rate after the task change. Quadratic acquisition (SA^2) and changes in the quadratic rate—reacquisition (RA^2)—after the task change were also examined. The performance trends across sessions are illustrated in Figure 1.

I tested a series of seven models similar to the recommendations of Bliese and Lang (2016). In Model 1, the basic growth model was tested including the SA, TA, RA, SA^2, and RA^2 terms. Only those growth terms that were statistically significant were retained in later models. In Model 2, the control variables GMA, videogame experience, and the Big Five personality variables were included. I then added trait interest and deprivation curiosity scores in Model 3. In Model 4, the main effects of the state interest-emotion, interest-cognition, deprivation-cognition, and deprivation-emotion dimensions (SIDECS) were added. Model 5 included the interactions between each of state dimensions with the SA growth term. Model 6 then included the interactions involving each of the state dimensions with the TA and RA growth terms. I compared AIC results across the models to aid in my interpretation of which predictors meaningfully and parsimoniously explained variance in performance.

Growth Trends

As shown in Model 1 of Table 9, there was a statistically significant positive SA effect ($B = 4.02$, $p < 0.01$), a statistically significant negative TA effect ($B = –14.43$, $p < .01$), and a statistically significant, negative RA effect ($B = –3.68$, $p < .01$). These effects together indicate that, across pre-change session, performance levels increased. However, after the task change, performance levels dropped markedly, and, although performance levels again began to rise, the rate of increase was significantly lower than that of the pre-change rate. SA^2 was significant ($B =$

–0.46, $p < .01$), which indicates that increases in performance decelerated across sessions. RA^2, however, was not significant and therefore was not included in any further model tests.

As shown in Model 2 of Table 9, the effects of GMA ($B = 0.39$, $p < .01$), videogame experience ($B = 3.53$, $p < .01$), and openness ($B = 1.38$, $p = .01$) were positive and statistically significant, meaning that higher GMA scores, videogame experience, and openness were associated with higher performance scores. Additionally, the main effects of extraversion ($B = –1.56$, $p < .01$) was negative and statistically significant, indicating that individuals that exhibited higher extraversion, had lower levels of performance. The effects for agreeableness and emotional stability were not statistically significant. As shown in Model 3 of Table 9, the effects of both trait interest and deprivation epistemic curiosity were not statistically significant.

Effects of State Epistemic Curiosity

As shown in Model 4 of Table 10, the main effect of interest-emotion ($B = 1.99$, $p < .05$) was positive and statistically significant, meaning that higher interest-emotion scores were associated with higher performance scores. Additionally, the main effect of deprivation-emotion ($B = –1.78$, $p < .05$) was negative and statistically significant, indicating that higher deprivation-emotion scores were associated with lower performance. Interest-cognition and deprivation-cognition did not yield statistically significant effects. Results of the AIC values showed improved fit for this model relative to previous models.

As shown in Model 5 of Table 10, there were no statistically significant SA interactions for any of the curiosity dimensions. However, as shown in Model 6 of Table 10, in the full model involving every curiosity dimensions and their respective interactions with the TA, RA, and SA growth terms, both the interest-emotion × SA ($B = 0.75$, $p < .01$) and interest-emotion × TA interactions ($B = –4.72$, $p < .05$) were statistically significant, showing that the linear growth in performance was stronger for participants with higher interest-emotions scores but with larger initial drops in performance (i.e., transition adaptation) after the change in task demands. No other interactions were statistically significant. The AIC for the full model was lower than that for any of the preceding models, showing additional support for the significance of the interest-emotion interactions with the SA and TA growth terms.

The interactions between interest-emotion curiosity and the SA and TA growth terms are illustrated in Figure 2 with all relevant main effects also modeled. Before the task change, individuals with higher interest-emotion curiosity exhibited notably more growth in performance, plateauing in the last two acquisition sessions. Not only did individuals lower in interest-emotion curiosity exhibit less growth in performance, but their growth in performance exhibited an inverted-U shape with slight losses in performance after plateauing in the middle acquisition sessions. Although individuals higher in interest-emotion curiosity exhibited a more pronounced decline in performance immediately after the task change, they exhibited gains in performance across the adaptation sessions while those lower in interest-emotion curiosity exhibited further declines in performance. Altogether, the effects show divergent patterns of growth for those higher versus lower in interest-emotion curiosity, reflecting substantial differences in persistence in skill acquisition and adaptation.

Short Form Development

Short forms are necessary for efficient administration of batteries in research when repeated measurement designs are needed to study phenomena. Examining the dynamic interplay among multiple self-regulation processes over the course of skill acquisition is an example of when shorts forms are needed. With respect to self-regulated learning, researchers are interested in tracking trajectories, disentangling within- from between-person effects, and examining cross-lagged relationships. In this way, the development of short forms is critical to advancing theory on state epistemic curiosity.

With the present data, I used a few different approaches in an attempt to develop short forms of each scale while balancing internal consistency reliability with predictive criterion-related validity. Specifically, I examined coefficient alphas and item-scale correlations (Smith et al., 2001), CFA factor loadings (Cann et al., 2010), item zero-order correlations with performance scores (Smith et al., 2001), and unique contributions to explaining performance scores using the machine learning Least Absolute Shrinkage and Selection Operator (LASSO) method (Putka et al., 2018) and stepwise regression (Kessler et al., 1998). For the LASSO method, α was set to be equal to 1 for all scales. The optimal tuning parameter, Lambda, was determined for each scale individually, interest-emotion (.43), interest-cognition (.65), deprivation-emotion (.65), and deprivation-cognition (.34) through a 2-fold cross validation.

I also looked at the wording of items with construct representativeness in mind. I wanted to limit the redundancy of construct space represented. That is, I was mindful of not creating scales using items with similar substantive words or meaning. With respect to reliability, I used a 95% confidence interval including .70 for alpha for the full scale as my minimally acceptable standard (Iacobucci & Duhachek, 2003). If the full scale yielded a 95% confidence interval that did not include an estimate of at least .70, then I would consider the development of a shorter scale to require writing new items. With this constraint in mind, I then took into account which combination of three or four items within each scale would maximize the variance explained in performance. Performance scores averaged across all sessions were used for these analyses. Tables 11-14 summarize the results.

As shown in Table 11, of the eight items for the interest-emotion scale, the results suggest a combination of items 5, 16, and 17 would provide a short scale with acceptable psychometric properties and construct representativeness. While the LASSO and stepwise results both pointed to using items 5 and 6, both items include the word “enjoy.” Items 16 and 17 both had item-scale correlations and CFA loadings greater than or equal to .70, both were retained in the LASSO results, and both provide complementary construct coverage. Using the Spearman-Brown prophecy formula (de Vet et al., 2017), shortening the number of items from eight to three would yield an estimated alpha reliability of .81.

As shown in Table 12, the development of a short scale for interest-cognition state epistemic curiosity requires writing additional items. For one, although the 95% confidence interval for alpha does include .70, the full scale involves only three items. Additionally, only one item, item 2, was retained in the LASSO and stepwise results. Neither of the other two items was retained in either the LASSO or stepwise results.

Similarly, the development of a short scale for deprivation-emotion state epistemic curiosity also requires writing additional items. As shown in Table 13, although the 95% confidence interval for alpha does include .70, only one item out of the five, item 8, yielded a positive zero-order correlation and positive LASSO and stepwise coefficients. All the other items yielded weak zero-order correlations with item 13 yielding negative LASSO and stepwise coefficients. With the lack of positive relationships with performance in mind, a look at the wording of the items suggests each reflects the experience of a negative emotion associating with feelings of deprivation but without any mention of effort to resolve the deprivation. In contrast, item 8 (i.e., “I will try to figure it out if something frustrates me about Unreal Tournament”) reflects the experience of a negative emotion coupled with effort to resolve the deprivation.

As shown in Table 14, of the eight items for the deprivation-cognition scale, the results suggest a combination of either items 7, 14, 15, and 20 or 7, 15, 19, and 20 would provide a short scale with acceptable psychometric properties and construct representativeness. The LASSO and stepwise results both pointed to using items 7 and 15. The LASSO results also suggested item 20 might be considered. Per the Spearman-Brown prophecy formula and the obtained alpha of .84, four items would be needed to achieve an estimated alpha of at least .70. Of the remaining items, 14 or 19 would be worth considering. On the one hand, item 14 (i.e., "I'm critical of ideas and approaches to playing Unreal Tournament") yielded weaker item-scale (.48), factor loading (.50), and zero-order (.17) estimates compared to those (.62, .75, and .23, respectively) for item 19 (i.e., I will keep trying hard until I fully understand Unreal Tournament), but on the other hand the choice between the two might depend on how well each represents a meaningfully distinct aspect of the construct space.

Discussion

The primary aim of this study was to create and validate a self-report state epistemic curiosity inventory, encompassing both interest and deprivation dimensions—the SIDECS. Whereas existing curiosity research has predominantly focused on interest and deprivation aspects, the results of the current study suggest future research that explores the additional distinction between cognitive and emotional aspects of state epistemic curiosity is worthwhile.

In the initial validation of the SIDECS, participants correctly sorted the items into the espoused dimensions, reflecting evidence of substantive content validity for the inventory and reaffirming Litman's (2008) demarcation between the interest and deprivation dimensions. While CFA of the SIDECS showed structural validity evidence for this two-dimensional framework over a unidimensional structure, CFA showed better fit with the addition of demarcating interest and deprivation dimensions into cognitive and emotional components. Such a four-factor framework affirms early claims (e.g., Berlyne, 1954) about epistemic curiosity involving a cognitive quest for answers and the emotions associated with getting answers and unresolving others. External validity evidence also showed support for the importance of distinguishing between cognition and emotion dimensions as indicated by the variation in the zero-order correlations with performance across the four dimensions. Results of the discontinuous growth curve analyses pointed to the importance of the emotional dimensions over the cognitive dimensions to skill acquisition and adaptative performance. In the sections below I provide a summary of how the results speak to the need for further scale development but nevertheless yield important theoretical implications.

Further Scale Development Needed

Because the CFA results yielded a four-factor model over the expected two-factor model, there were necessarily fewer items left per scale than expected. Coupled with the results of the additional short-form analyses, it is clear that two of the four scales need further item development and evaluation of basic psychometric properties. Specifically, more items need to be written for the interest-cognition and deprivation-emotion scales. The three-item interest-cognition scale had a low coefficient alpha reliability (.66) and only one item retained in the LASSO and stepwise regression analyses. Further research on interest-cognition curiosity likely requires at least five additional items. Per the Spearman-Brown prophecy formula, an additional five items would increase the scale's reliability to .83, commensurate with the reliability of the deprivation-cognition scale. Examples of additional items adapted from Litman and Spielberger (2003) that could be included in the interest-cognition scale would be, "I want to discover how things work in Unreal Tournament," "When something unexpected happens in Unreal

Tournament, I try to figure out what caused it," and "With Unreal Tournament, I turn ideas over and think about them in different ways."

The five-item deprivation-emotion scale had a questionable coefficient alpha reliability (.70), but the more troubling finding is that it only had one item (i.e., item 8, "I will try to figure it out if something frustrates me about Unreal Tournament") retained in the LASSO and stepwise analyses with a positive weight. In fact, it was the only item with a positive zero-order correlation with performance. All the other items either had weak and non-significant negative zero-order correlations with performance, one of which was retained with a negative weight in the LASSO and stepwise results. As such, further research on deprivation-emotion curiosity also requires at least five additional items. Per the Spearman-Brown formula, the alpha scores for reliability would be .82 with the addition of five more items. In this vein, it is difficult to draw firm conclusions about the negative main effect for deprivation-emotion curiosity from the discontinuous growth curve analyses.

Two approaches for item development could be taken to examine the connection between negative emotions and the effort to resolve deprivation shown in item 8. Negative emotions may provide the drive to overcome the obstacles and unresolved questions faced. Example items of this could include "I have frustrations about Unreal Tournament that make me want to learn more about it" and "There are things I struggle with in Unreal Tournament that motivate me to keep trying." Negative emotions may simply be experienced alongside effort allocated to learning. Example items adapted from Litman and Jimerson (2004) and Naylor (1981) of this could include, "Even if it bugs me, I keep at it when I don't quite understand something about Unreal Tournament" and "I feel puzzled about Unreal Tournament as I piece it together." Including these items would provide more robust tests of the deprivation-emotion scale.

In contrast, the results suggest that neither the interest-emotion nor deprivation-cognition scales need additional items. Both yielded strong lower bound 95% confidence intervals for coefficient alpha reliability estimates (.91 and .80, respectively), and both yielded viable three-to-four item short forms. However, given their conceptual and empirical relationships with the interest-cognition and deprivation-emotion dimensions, future discoveries on the roles played by interest-emotion and deprivation-cognition curiosity will be limited to the extent that research using these scales does not involve viable scales for the other two dimensions. Simply put, further theory on state epistemic curiosity will be arrested without further scale development.

Implications for Theory

The significant relationships with performance for SIDECS scores coupled with its weak and generally nonsignificant correlations with dispositional variables including trait curiosity point to the importance of using state scales to advance theory on epistemic curiosity. The finding that trait epistemic curiosity scores were not associated with performance corroborates the importance of state scales and supports Naylor's (1981) contention that state and trait curiosity should be distinguished from each other. The lack of significant correlations between dispositional factors like openness, cognitive ability, and trait curiosity with SIDECS scores coupled with SIDECS scores correlating with performance indicates that state epistemic curiosity is more about the individual's relationship with a task at hand and less of a mediator between distal factors and performance. Overall, the initial validation evidence of the SIDECS supports Loewenstein's (1994) recommendation to frame curiosity measures in reference to specific criterion tasks.

It is important to acknowledge that previously developed state scales often exhibit strong correlations with their trait counterparts (Grös et al., 2007; Krohne et al., 2001). The weak and non-significant correlations observed between the four dimensions and the trait scales might be attributed to task-specific modifications. Items on previously developed state scales are not framed in terms of a given task at hand. For instance, while the trait epistemic curiosity item "I enjoy exploring new ideas" may be broadly applicable, the state task-specific counterpart, "It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me," may vary in relevance based on an individual's perspective on the given task. In this way, following Loewenstein’s (1994) recommendation to frame items in terms of a specific task or context will likely yield stronger and more theoretically sensible correlations with learning and performance outcomes. In general, the extent to which scores from state-based curiosity measures correlate with scores from other measures very likely depends on the extent to which items on the measures are similarly framed.

Despite concerns about the deprivation-emotion items, the incremental validity of the interest-emotion and deprivation-emotion scores from the growth curve analysis extends theory on epistemic curiosity’s role in learning and achievement contexts (e.g., Berlyne, 1954; Loewenstein, 1994). The findings highlight the importance of distinguishing emotional and cognitive components. In particular, the results suggest state epistemic curiosity’s role is more emotional than cognitive. However, given the strong intercorrelations among the four dimensions, validated scales for all four dimensions in longitudinal designs is needed to better examine the dynamic interplay that might exist among the emotion and cognition components and with other affective (e.g., self-efficacy) and cognitive (e.g., metacognition) self-regulation variables.

The significance of interest-emotion in the prediction of performance, illustrated in Figure 2, suggests persistence which further embeds epistemic curiosity as an important aspect of motivation. Graham and Weiner (1996) emphasized that motivational theory must include the intensity of the behavior, persistence of behavior, and the cognitions and emotional reactions accompanying behavior, which is utilized to explain why some individuals persist despite incredibly difficult tasks and why others give up when the most subtle problem emerges. The discrepancy between those with high and low interest-emotion in their persistence describes these features.

Huck et al. (2020) found that interest curiosity better predicted skill acquisition and adaptation than deprivation curiosity. The current study reaffirms the importance of curiosity stemming from interest as an important predictor skill acquisition and performance outcomes, but given the aforementioned problems with the deprivation-emotion scale it is difficult to make firm conclusions regarding the relative importance of deprivation aspects of curiosity. Due to the lack of research examining relationships of state-based interest and deprivation dimensions with learning and performance outcomes, there is little support for or against the importance of deprivation curiosity. However, the current results suggest that deprivation-cognition curiosity is not directly related to skill acquisition or adaptation. Perhaps with improved scales for interest-cognition and deprivation-emotion curiosity, future research with longitudinal designs that can disentangle within-person from between-person effects (see Hardy et al., 2019 as an example) might show how deprivation-cognition plays more of an indirect role alongside other curiosity dimensions.

Limitations and Future Directions

It is certainly important to acknowledge the limitations of the present research. First, given the all-male and predominantly Caucasian sample and the use of a first-person shooter computer game as a criterion task, it is important to recognize the need for future research to involve samples more representative of a broader population and examine learning and performance across a range of tasks and achievement contexts.

Second, data from SIDECS were collected at a single time point between the end of the acquisition sessions and the start of the adaptation sessions. Future research should use repeated measurement occasions and longitudinal designs from the start of acquisition to examine how differences in how dimensions fluctuate and relate to performance and other variables of interest. The unexpected task change midway through the study also might introduce confounding variables that influence curiosity’s association with other variables. For example, much of the observed interest-emotion interaction with the SA growth term was empirically postdictive in nature rather than predictive. Scores taken around the start of acquisition might yield different or nonsignificant interactions with growth terms.

Third, while the criterion performance task, UT2004, provides a complex and dynamic learning environment, it may not represent the range of knowledge and skills and learning activities involving curiosity in other contexts. Accordingly, adapting the SIDECS for research in other learning and performance contexts would go a long way toward testing the extent to which the correlations it yields with performance are generalizable. In the same vein, the present study is limited in that it did not examine relationships with specific self-regulation variables or learning behaviors, such as motivation to explore, ask questions, or engage in creative problem-solving, potentially overlooking other aspects of curiosity’s impact. For instance, the fast-paced nature of UT2004 and its strong perceptual-motor demands are likely associated with more incidental or implicit learning processes than with more deliberate and explicit processes.

With improvements to the interest-cognition and deprivation-emotion scales, future research can use the SIDECS inventory to test specific hypotheses and extend theory concerning curiosity. For instance, Loewenstein (1994) described the enhancement of state epistemic curiosity through questions and feedback via revealing information gaps, but little to no empirical research has been conducted that describes how curiosity is impacted by particular types of questions and feedback and in turn how curiosity affects future learning. Similar to notions of flow (Csikszentmihalyi, 1997), such research could also address Day's (1982) notions concerning what the ideal epistemic curiosity state looks like in relation to anxiety and boredom across a range of learning, achievement, and creative contexts.

Conclusion

This study aimed to develop a state-based self-report inventory of epistemic curiosity, referred to as the SIDECS, for researchers seeking to contribute to the expansion of current theories of self-regulated learning and performance. Specifically, I aimed to distinguish between the dimensions of interest and deprivation, but empirically the data better reflected a four-factor structure with both the interest and deprivation dimensions bifurcated into cognition and emotion components. Thus, the SIDECS includes four scales: interest-emotion, interest-cognition, deprivation-emotion, and deprivation-cognition. While this study's initial validation efforts showed support for the interest-emotion and deprivation-cognition scales including short-form versions, more work including item writing is needed for the interest-cognition and deprivation-emotion scales. In particular, the results pointed to the importance of interest-emotion curiosity to persistence, showing positive effects on performance that increased over the course of learning a complex computer game and adapting to changes in task demands. With further development and validation efforts on the interest-cognition and deprivation-emotion scales in mind, I hope the present study inspires future research, particularly longitudinal investigations using repeated measures of all four scales, that expands theory on the roles played by curiosity in phenomena related to self-regulation, learning, achievement, and creativity.

References

American Society for Training and Development (2015). *2015 State of the Industry Report*. Alexandria, VA: American Society for Training and Development.

Anderson, J. C., & Gerbing, D. W. (1991). Predicting the performance of measures in a confirmatory factor analysis with a pretest assessment of their substantive validities. *Journal of Applied Psychology*, *76*, 732-740. https://doi.org/10.1037/0021-9010.76.5.732

Appriou, A., Ceha, J., Pramij, S., Dutartre, D., Law, E., Oudeyer, P.-Y., & Lotte, F. (2020, October). Towards measuring states of epistemic curiosity through electroencephalographic signals. In *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 4006-4011). IEEE.

Bell, B. S., Kanar, A. M., & Kozlowski, S. W. J. (2008). Current issues and future directions in simulation-based training in North America. *The International journal of Human Resource Management*, *19*(8), 1416-1434. https://doi.org/10.1080/09585190802200173

Berlyne, D. E. (1954). A theory of human curiosity. *British journal of psychology*, *45*(3), 180-191.

Berlyne, D. E. (1962). Uncertainty and epistemic curiosity. *British Journal of Psychology*, *53*(1), 27-34. https://doi.org/10.1111/j.2044-8295.1962.tb00811.x

Berlyne, D. E. (1966). Curiosity and exploration: Animals spend much of their time seeking stimuli whose significance raises problems for psychology. *Science*, *153*(3731), 25-33.

Bliese, P. D., & Lang, J. W. B. (2016). Understanding relative and absolute change in discontinuous growth models: Coding alternatives and implications for hypothesis testing. *Organizational Research Methods*, *19*(4), 562-592. https://doi.org/10.1177/1094428116633502

Borowske, K. (2005). Curiosity and motivation-to-learn.

Boyle, G. J. (1983). Critical review of state-trait curiosity Test development. *Motivation and Emotion*, *7*(4), 377-397. https://doi.org/10.1007/BF00991647

Boyle, G. J. (1989). Breadth-depth or state-trait curiosity? A factor analysis of state-trait curiosity and state anxiety scales. *Personality and Individual Differences*, *10*(2), 175-183. https://doi.org/10.1016/0191-8869(89)90201-8

Browns, R., Loeffelman, J. E., Steinley, D., & Sher, K. J. (2021). A brief young adult alcohol problems screening test: Short form development using combinatorics. *Journal of American College Health*, 1-7. https://doi.org/10.1080/07448481.2022.2095870

Cann, A., Calhoun, L. G., Tedeschi, R. G., Taku, K., Vishnevsky, T., Triplett, K. N., & Danhauer, S. C. (2010). A short form of the posttraumatic growth inventory. *Anxiety, Stress, & Coping*, *23*(2), 127-137. https://doi.org/10.1080/10615800903094273

Chamorro-Premuzic, T., Furnham, A., & Ackerman, P. L. (2006). Incremental validity of the typical intellectual engagement scale as predictor of different academic performance measures. *Journal of Personality Assessment*, *87*(3), 261-268. https://doi.org/10.1207/s15327752jpa8703_07

Cohen, A. R., Stotland, E., & Wolfe, D. M. (1955). An experimental investigation of need for cognition. *The Journal of Abnormal and Social Psychology*, *51*(2), 291-294. https://doi.org/10.1037/h0042761

Colquitt, J. A., Sabey, T. B., Rodell, J. B., & Hill, E. T. (2019). Content validation guidelines: Evaluation criteria for definitional correspondence and definitional distinctiveness. *Journal of Applied Psychology, 104,* 1243-1265. https://doi.org/10.1037/apl0000406

Cortina, J. M., Sheng, Z., Keener, S. K., Keeler, K. R., Grubb, L. K., Schmitt, N., ... & Banks, G. C. (2020). From alpha to omega and beyond! A look at the past, present, and (possible) future of psychometric soundness in the Journal of Applied Psychology. *Journal of Applied Psychology*, *105*, 1351-1381. http://dx.doi.org/10.1037/apl0000815

Csikszentmihalyi, M. (1997). Flow and the psychology of discovery and invention. *HarperPerennial*, *New York*, 39, 1-16.

Day, H. I. (1982). Curiosity and the interested explorer. *Performance & Instruction*, *21*(4), 19-22. https://doi.org/10.1002/pfi.4170210410

de Vet, H. C. W., Mokkink, L. B., Mosmuller, D. G., & Terwee, C. B. (2017). Spearman-Brown prophecy formula and Cronbach's alpha: different faces of reliability and opportunities for new applications. *85*, 45-49. https://doi.org/10.1016/j.jclinepi.2017.01.013

Di Leo, I., Muis, K. R., Singh, C. A., & Psaradellis, C. (2019). Curiosity… confusion? Frustration! The role and sequencing of emotions during mathematics problem solving. *Contemporary Educational Psychology*, *58*, 121-137. https://doi.org/10.1016/j.cedpsych.2019.03.001

Epic Games (2004). Unreal tournament 2004. Atari, Midway.

Fisher, K. M. (2000). Curiouser and curiouser: The virtue of wonder. Journal of Education, 182(2), 34-42. https://doi.org/10.1177/002205740018200020

Frey, M. C., & Detterman, D. K. (2004). Scholastic assessment or g? The relationship between the scholastic assessment test and general cognitive ability. *Psychological Science*, *15*(6), 373-378. https://doi.org/10.1111/j.0956-7976.2004.00687.x

Gardner, D. G., Cummings, L. L., Dunham, R. B., & Pierce, J. L. (1998). Single-item versus multiple-item measurement scales: An empirical comparison. *Educational and*

Psychological Measurement, *58*(6), 898-915. https://doi.org/10.1177/00131644980580060

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment*, *4*(1), 26-42. https://doi.org/10.1037/1040-3590.4.1.26

Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences*, *17*(11), 585-593. https://doi.org/10.1016/j.tics.2013.09.001

Graham, S., & Weiner, B. (1996). Theories and principles of motivation. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 63-84). Macmillan Library Reference Usa; Prentice Hall International.

Gross, M. E., Zedelius, C. M., & Schooler, J. W. (2020). Cultivating an understanding of curiosity as a seed for creativity. *Current Opinion in Behavioral Sciences*, *35*, 77-82. https://doi.org/10.1016/j.cobeha.2020.07.015

Grossnickle, E. M. (2016). Disentangling curiosity: Dimensionality, definitions, and distinctions from interest in educational contexts. Educational Psychology Review, 28(1), 23-60. https://doi.org/10.1007/s10648-014-9294-y

Grös, D. F., Antony, M. M., Simms, L. J., & McCabe, R. E. (2007). Psychometric properties of the state-trait inventory for cognitive and somatic anxiety (STICSA): Comparison to the state-trait anxiety inventory (STAI). *Psychological Assessment*, *19*(4), 369-381. https://doi.org/10.1037/1040-3590.19.4.369

Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of curiosity modulate hippocampus-dependent learning via the dopaminergic circuit. *Neuron*, *84*(2), 486-496. https://doi.org/10.1016/j.neuron.2014.08.060

Hagtvedt, L. P., Dossinger, K., Harrison, S. H., & Huang, L. (2019). Curiosity made the cate more creative: Specific curiosity as a driver of creativity. *Organizational Behavior and Human Decision Processes*, *150*, 1-13. https://doi.org/10.1016/j.obhdp.2018.10.007

Hardy, J. H., III, Ness, A. M., & Mecca, J. (2017). Outside the box: Epistemic curiosity as a predictor of creative problem solving and creative performance. *Personality and Individual Differences*, *104*, 230-237. https://doi.org/10.1016/j.paid.2016.08.004

Hardy, J. H., III, Day, E. A., & Steele, L. M. (2018). Interrelationships among self-regulated learning processes: Toward a dynamic process-based model of self-regulated learning. *Journal of Management*, *45*(8), 3146-3177. https://doi.org/10.1177/0149206318780440

Hardy J. H., III, Day, E. A., & Arthur Jr, W. (2019). Exploration-exploitation tradeoffs and information-knowledge gaps in self-regulated learning: Implications for learner-controlled training and development. *Human Resources Management Review*, *29*(2), 196-217. https://doi.org/10.1016/j.hrmr.2018.07.004

Hardy, J. H., III, Day, E. A., North, M. N., & Rockwood, J. (2023). Unpacking on-task effort in performance-based learning: Information-knowledge gaps guide effort allocation decisions. *Journal of Applied Psychology*. Advance online publication. https://doi.org/10.1037/apl0001140

Hardy, J. H., III, Day, E. A, Hughes, M. G., Wang, X., & Schuelke, M. J. (2014). Exploratory behavior in active learning: A between- and within-person examination. *Organizational Behavior and Human Decision Processes*, *125*, 98-112. http://dx.doi.org/10.1016/j.obhdp.2014.06.005

Hartmann, T., & Klimmt, C. (2006). Gender and computer games: Exploring females' dislikes. *Journal of Computer-mediated communication*, *11*(4), 910-931.

https://doi.org/10.1111/j.1083-6101.2006.00301.x

Hong, J.-C., Hwang, M.-Y., Liu, Y.-H., & Tai, K.-H. (2020). Effects of gamifying questions on English grammar learning mediated by epistemic curiosity and language anxiety. *Computer Assisted Language Learning*, 1-25. https://doi.org/10.1080/09588221.2020.1803361

Hopp, T., & Fisher, J. (2017). Examination of the relationship between gender, performance, and enjoyment of a first-person shooter game. *Simulation & Gaming*, *48*(3), 338-362. https://doi.org/10.1177/1046878117693

Howe, M. (2019). General mental ability and goal type as antecedents of recurrent adaptive task performance. *Journal of Applied Psychology*, *104*(6), 796-813. https://doi.org/10.1037/apl0000379

Huck, J. T., Day, E. A., Lin, L., Jorgensen, A. G., Westlin, J., & Hardy III, J. H. (2020). The role of epistemic curiosity in game-based learning: Distinguishing skill acquisition from adaptation. *Simulation & Gaming*, *51*(2), 141-166. https://doi.org/10.1177/1046878119895557

Hughes, M. G., Day, E. A., Wang, X., Schulke, M. J., Arsenault, M. L., Harkrider, L. N., & Cooper, O. D. (2013). Learner-controlled practice difficulty in the training of a complex task: Cognitive and motivational mechanisms. *Journal of Applied Psychology*, *98*(1), 80-98. https://doi.org/10.1037/a0029821

James, W., Burkhardt, F., Bowers, F. & Skrupskelis, I. K. (1890). *The principles of psychology* (Vol. 1, No. 2). London: Macmillan.

Johnson, J. (2016). *Novel behavioral measure of specific and diversive curiosity and its correlation to academic performance.* [Unpublished undergraduate honors thesis]. University of Colorado Boulder.

Jorgensen, A., Day, E. A., Huck, J. T., Westlin, J., Richels, K., & Nguyen, C. (2021). Emotion-performance relationships in the acquisition and adaptation of a complex skill: Are relationships dynamic and dependent on activation potential?. *Human Performance*, *34*(1), 25-28. https://doi.org/10.1080/08959285.2020.1823985

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The wick in the candle of learning: Epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963-973. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kashdan, T. B., DeWal, C. N., Pond, R. S., Silvia, P. J., Lambert, N. M., Fincham, F. D., Savostyanova, A. A., & Keler, P. S. (2013). Curiosity protects against interpersonal aggression: Cross-sectional, daily process, and behavioral evidence. Journal of Personality, 81(1), 87-102. https://doi.org/10.1111/j.1467-6494.2012.00783.x

Keith, N., & Wolff, C. 2015. Encouraging active learning. In K. Kraiger, J. Passmore, N. R. dos Santos, & Malvezzi (Eds.), *The Wiley-Blackwell handbook of training, development, and performance improvement* (pp. 92-116). Wiley-Blackwell

Kessler, R. C., Mroczek, D., Ustun, B., & Wittchen, H. U. (1998). The world health organization composite international diagnostic interview short-form (CIDI-SF). *International Journal of Methods in Psychiatric Research*, *7*(4), 171-184. https://doi.org/10.1002/mpr.47

Koenig, K. A., Frey, M. C., & Detterman, D. K. (2008). ACT and general cognitive ability. *Intelligence*, *36*, 153-160. https://doi.org/10.1016/j.intell.2007.03.005

Krohne, H. W., Schmukle, S. C., Spaderna, H., & Spielberger, C. D. (2002). The state-trait depression scales: An international comparison. *Anxiety, Stress and Coping*, *15*(2), 105-122. https://doi.org/10.1080/10615800290028422

Lang, J. W. B., & Bliese, P. D. (2009). General mental ability and two types of adaptation to unforeseen change: Applying discontinuous growth models to the task-change paradigm. *Journal of Applied Psychology*, *94*(2), 411-428. https://doi.org/10.1037/a0013803

Leherissey, B. L. (1971). The development of a measure of state epistemic curiosity. (Tech. Memorandum No. 34). Tallahassee: Florida State University.

Lester, D. (1968). The effect of fear and anxiety on exploration and curiosity: Toward a theory of exploration. The Journal of General Psychology, 79, 105-120. https://doi.org/10.1080/00221309.1968.9710458

Litman, J. A. (2008). Interest and deprivation factors of epistemic curiosity. *Personality and Individual Differences*, *44*(7), 1585-1595. https://doi.org/10.1016/j.paid.2008.01.014

Litman, J. A., & Jimerson, T. L. (2004). The measurement of curiosity as a feeling of deprivation. *Journal of Personality Assessment*, *82*(2), 147-157. https://doi.org/10.1207/s15327752jpa8202_3

Litman, J. A., & Mussel, P. (2013). Validity of the interest- and deprivation-type epistemic curiosity model in Germany. *Journal of Individual Difference*, *34*(2), 59-68. https://doi.org/10.1027/1614-0001/a000100

Litman, J. A., & Silvia, P. J. (2006). The latent structure of trait curiosity: Evidence for interest and deprivation curiosity dimensions. *Journal of Personality Assessment*, *86*(3), 318-328. https://doi.org/10.1207/s15327752jpa8603_07

Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of Personality Assessment*, *80*(1), 75-86. https://doi.org/10.1207/S15327752JPA8001_16

Litman, J. A., Crowson, H. M., & Kolinski, K. (2010). Validity of the interest- and deprivation-type epistemic curiosity distinction in non-students. *Personality and Individual Differences*, *49*, 531-536. https://doi.org/10.1016/j.paid.2010.05.021

Litman, J. A., Hutchins, T. L., & Russon, R. K. (2005). Epistemic curiosity, feeling-of-knowing, and exploratory behaviour. *Cognition and Emotion*, *19*(4), 559-582. https://doi.org/10.1080/02699930441000427

Little, E. B., & Creaser, J. W. (1968). Epistemic curiosity and man's higher nature. Psychological Reports, 23(2), 615-624. https://doi.org/10.2466/pr0.1968.23.2.615

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*(1), 75-98. https://doi.org/10.1037/0033-2909.116.1.75

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130-149. https://doi.org/10.1037/1082-989X.1.2.130

Markey, A., & Loewenstein, G. (2014). Curiosity. In R. Pekrun & L. Linnenbrink-Garcia (Eds.) *International Handbook of Emotions in Education* (pp. 228-245). Routledge/Taylor & Francis Group.

Metcalfe, J., Schwartz, B. L., & Eich, T. S. (2020). Epistemic curiosity and the region of proximal learning. *Current Opinion in Behavioral Sciences*, *35*, 40-47. https://doi.org/10.1016/j.cobeha.2020.06.007

Mussel, P., Spengler, M., Litman, J. A., & Heinz Schuler (2011). Development and validation of the German work-related curiosity scale. *European Journal of Psychological Assessment, 28*(2), 109-117. https://doi.org/10.1027/1015-5759/a000098

Mussel, P. (2010). Epistemic curiosity and related constructs: Lacking evidence of discriminant validity. *Personality and Individual Differences*, *49*(5), 506-510. https://doi.org/10.1016/j.paid.2010.05.014

Mussel, P. (2013). Introducing the construct curiosity for predicting job performance. *Journal of Organizational Behavior*, *34*(4), 453-472. https://doi.org/10.1002/job.1809

Naylor, F. D. (1981). A state-trait curiosity inventory. *Australian Psychologist*, *16*(2), 172-183. https://doi.org/10.1080/00050068108255893

Peterson, E. G. (2020). Supporting curiosity in schools and classrooms. *Current Opinion in Behavioral Sciences*, *35*, 7-13. https://doi.org/10.1016/j.cobeha.2020.05.006

Putka, D. J., Beatty, A. S., & Reeder, M. C. (2018). Modern prediction methods: New perspectives on a common problem. *Organizational Research Methods*, *21*(3), 689-732. https://doi.org/10.1177/109442811769704

Reio, T. G., & Wiswell, A. (2000). Field investigation of the relationship among adult curiosity, workplace learning, and job performance. *Human Resource Development Quarterly*, *11*(1), 5-30. https://doi.org/10.1002/1532-1096(200021)11:1<5::AID-HRDQ2>3.0.CO;2-A

Renner, B. (2006). Curiosity about people: The development of a social curiosity measure in adults. Journal of Personality Assessment, 87(3), 305-316. https://doi.org/10.1207/s15327752jpa8703_11

Renninger, K., Sansone, C., & J. L. Smith (2004). Love of learning. In C. Peterson & M. E. P. Seligman (Eds.), *Character strengths and virtues: A classification and handbook* (pp. 161-179). New York: Oxford University Press.

Richels, K. A., Day, E. A., Jorgensen, A. G., & Huck, J. T. (2020). Keeping calm and carrying on: Relating affect spin and pulse to complex skill acquisition and adaptive performance. *Frontiers in Psychology*, *11*, 1-17. https://doi.org/10.3389/fpsyg.2020.00377

Ross, W. D. (Ed.). (1924). Aristotle's metaphysics (Vol. 2). Clarendon Press.

Rule, A. C., & Barrera III, M. T. (2008). Three Authentic Curriculum-Integration Approaches to Bird Adaptations That Incorporate Technology and Thinking Skills. *Online Submission*.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research*, *8*(2), 23-74.

Schmidt, H. G., & Rotgans, J. I. (2021). Epistemic curiosity and situational interest: Distant cousins or identical twins? *Educational Psychology Review*, *33*, 325-352. https://doi.org/10.1007/s10648-020-09539-9

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, *58*, 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Shin, D. D., & Kim, S. (2019). Homo Curious: Curious or Interested?. *Educational Psychology Review*, *31*(4), 853-874. https://doi.org/10.1007/s10648-019-09497-x

Silvia, P. J. (2012). Curiosity and motivation. *The Oxford handbook of human motivation*, 157-166.

Smith, G. T., McCarthy, D. M., & Anderson, K. G. (2000). On the sins of short-form development. *Psychological Assessment*. *12*(1), 102-111. https://doi.org/10.1037/1040-3590.12.1.102

Spielberger, C. D., & Starr, L. M. (2012). Curiosity and exploratory behavior. In *Motivation: Theory and research* (pp. 231-254). Routledge.

Steele, L. M., Hardy III, J. H., Day, E. A., & Watts, L. L. (2019). Navigating creative paradoxes: Exploration and exploitation effort drive novelty and usefulness. *Psychology of Aesthetics, Creativity, and the Arts*, *15*(1), 149-164. https://doi.org/10.1037/aca0000236

Von Stumm, S., Hell, B., & Chamorro-Premuzic, T. (2011). The hungry mind: Intellectual curiosity is the third pillar of academic performance. *Perspectives on Psychological Science*, *6*(6), 574-588. https://doi.org/10.1177/1745691611421204

Wagstaff, M. F., Flores, G. L., Ahmed, R., & Villanueva, S. (2020). Measures of curiosity: A literature review. *Human Resource Development Quarterly*, *32*(3), 363-389. https://doi.org/10.1002/hrdq.21417

Westlin, J., Day, E. A., & Hughes, M. G. (2019). Learner-controlled practice difficulty and task exploration in an active-learning gaming environment. *Simulation & Gaming*, *50*(6), 812-831. https://doi.org/10.1177/1046878119877672

Table 1

Chronological List of Initial Scale Development Articles for Measuring Epistemic Curiosity

Scale name	State/ Trait	Dimensionality	Dimensions measured	Reliability	Validation evidence	Source
State Curiosity Scale	State	Single	—	α = .87-.89	Convergent	Leherissey, 1971
Melbourne Curiosity Inventory	State	Single	—	α = .89-.92 retest = .77-.83	Factor-analytic	Naylor, 1981
State-Trait Personality Inventory	State	Single	—	α = .78-.84	Factor-analytic	Boyle, 1983
Epistemic Curiosity Scale	Trait	Multi	Specific Diversive	α = .80-.96	Convergent Discriminant	Litman & Spielberger, 2003
Curiosity as a Feeling of Deprivation	Trait	Multi	Intolerance Competence Problem-solving	α = .64-.84	Factor-analytic Convergent Discriminant	Litman & Jimerson, 2004
Epistemic Curiosity	Trait	Multi	Interest Deprivation	α > .70	Factor-analytic Convergent Discriminant	Litman, 2008
Epistemic Curiosity	State	Single	—	*H* = .92	Factor-analytic Convergent	Schmidt & Rotgans, 2020

Note. *H* = Hancock and Mueller (2001).

Table 2

SIDECS Interest Scale Sources

Item	Source adaptation
11. I enjoy trying new ideas for playing Unreal Tournament.	Huck et al. (2020); Litman (2008); Litman & Spielberger (2003)
16. It is fascinating when I learn something new about Unreal Tournament.	Huck et al. (2020); Litman (2008); Litman & Spielberger (2003)
5. It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.	Huck et al. (2020); Litman (2008); Litman & Spielberger (2003)
6. I would enjoy discussing Unreal Tournament with others.	Huck et al. (2020); Litman (2008); Litman & Spielberger (2003)
2. When I learn something new about Unreal Tournament, I like to find out more about it.	Huck et al. (2020); Litman (2008); Litman & Spielberger (2003)
17. Unreal Tournament is intriguing to me.	Naylor (1981)
23. I feel inquisitive about Unreal Tournament.	Naylor (1981)
10. It is fun to discover new things about Unreal Tournament.	Litman & Spielberger (2003)
9. New ideas about Unreal Tournament excite my imagination.	Litman & Spielberger (2003)
12. I think about hypothetical situations within Unreal Tournament.	Litman & Spielberger (2003)
21. I think about what might happen in Unreal Tournament if I try a new idea.	Litman & Spielberger (2003)

Note. The participant is told to respond to these items on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree. The numbering to the left of the items reflects the randomized order presented to participants.

Table 3

SIDECS Deprivation Scale Sources

Item	Source adaptation
1. With Unreal Tournament, I feel restless without answers to the problems I have.	Huck et al. (2020); Litman (2008); Litman & Jimerson (2004); Problem-Solving*
22. I dwell about being able to play Unreal Tournament better.	Huck et al. (2020); Litman (2008); Litman & Jimerson (2004); Problem-Solving*
4. I can't stop thinking about the challenges to playing Unreal Tournament.	Huck et al. (2020); Litman (2008); Litman & Jimerson (2004); Problem-Solving*
8. I will try to figure it out if something frustrates me about Unreal Tournament.	Huck et al. (2020); Litman (2008); Litman & Jimerson (2004); Intolerance*
7. I work like a beast at aspects of Unreal Tournament that I feel must be solved.	Huck et al. (2020); Litman (2008); Litman & Jimerson (2004); Intolerance*
13. It aggravates me if I can't remember something about Unreal Tournament.	Litman & Jimerson (2004) Intolerance*
3. It gets on my nerves when I'm close to understanding something in Unreal Tournament but can't quite figure it out.	Litman & Jimerson (2004) Intolerance*
14. I'm critical of ideas and approaches to playing Unreal Tournament.	Litman & Jimerson (2004) Intolerance*
20. I will keep trying hard until I fully understand Unreal Tournament.	Litman & Jimerson (2004) Competence*
18. I feel uncomfortable when I don't understand something about Unreal Tournament.	Litman & Jimerson (2004) Competence*
19. When something puzzles me about Unreal Tournament, I think about it until I understand it.	Litman & Jimerson (2004) Competence*
15. There are gaps in my understanding of Unreal Tournament that I want to fill.	Original
24. I want answers for how to play Unreal Tournament better.	Naylor (1981)

Note. The participant is told to respond to these items on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree. *Litman & Jimerson (2004) deprivation subdimensions. The numbering to the left of the items reflects the randomized order presented to participants.

Table 4

Substantive Content Results for the SIDECS Interest Scale

Item	Interest	Deprivation	p_{sa}	c_{sv}
I enjoy trying new ideas for playing Unreal Tournament.	16	0	1.00	1.00
It is fascinating when I learn something new about Unreal Tournament.	15	1	0.94	0.88
It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.	14	2	0.88	0.75
I would enjoy discussing Unreal Tournament with others.	15	1	0.94	0.88
When I learn something new about Unreal Tournament, I like to find out more about it.	13	3	0.81	0.63
Unreal Tournament is intriguing to me.	15	1	0.94	0.88
I feel inquisitive about Unreal Tournament.	14	1	0.93	0.87
It is fun to discover new things about Unreal Tournament.	15	1	0.94	0.88
New ideas about Unreal Tournament excite my imagination.	15	1	0.94	0.88
I think about hypothetical situations within Unreal Tournament.	14	1	0.93	0.87
I think about what might happen in Unreal Tournament if I try a new idea.	15	1	0.94	0.88

Note. p_{sa} is the proportion of substantive agreement. c_{sv} is the substantive-validity coefficient. The data was collected using Anderson and Gerbing's (1991) method in obtaining evidence for substantive content validity. "Interest" and "Deprivation" columns represent the number of individuals who sorted the item into the specified dimension.

Table 5

Substantive Content Results for the SIDECS Deprivation Scale

Item	Interest	Deprivation	p_{sa}	c_{sv}
With Unreal Tournament, I feel restless without answers to the problems I have.	0	15	1.00	1.00
I dwell about being able to play Unreal Tournament better.	1	14	0.93	0.87
I can't stop thinking about the challenges to playing Unreal Tournament.	3	13	0.81	0.63
I will try to figure it out if something frustrates me about Unreal Tournament.	2	13	0.87	0.73
I work like a beast at aspects of Unreal Tournament that I feel must be solved.	1	14	0.93	0.87
It aggravates me if I can't remember something about Unreal Tournament.	1	14	0.93	0.87
It gets on my nerves when I'm close to understanding something in Unreal Tournament but can't quite figure it out.	1	14	0.93	0.87
I'm critical of ideas and approaches to playing Unreal Tournament.	3	13	0.81	0.63
I want to keep learning until I fully understand Unreal Tournament.	3	13	0.81	0.63
When something puzzles me about Unreal Tournament, I think about it until I understand it.	4	12	0.75	0.50
There are gaps in my understanding of Unreal Tournament that I want to fill.	3	13	0.81	0.63
I want answers for how to play Unreal Tournament better.	2	14	0.88	0.75

Note. p_{sa} is the proportion of substantive agreement. c_{sv} is the substantive-validity coefficient. The data was collected using Anderson and Gerbing's (1991) method in obtaining evidence for substantive content validity. "Interest" and "Deprivation" columns represent the number of individuals who sorted the item into the specified dimension.

Table 6

Model Fit of State Epistemic Curiosity Models for the SIDECS Inventory

Model	χ^2	*df*	χ^2/df	CFI	TLI	RMSEA	RMSEA 90% Upper CI	SRMR	AIC	$\Delta\ \chi^2$
A priori										
1 factor	804.27	252	3.19	.81	.79	.094	.101	.08	15432.95	
2-factor uncorrelated	768.45	252	3.05	.82	.80	.091	.098	.24	15397.14	35.82
2-factor correlated	602.94	251	2.40	.88	.87	.075	.083	.07	15233.63	165.51*
Post hoc alternative										
4-factor correlated	554.88	246	2.26	.89	.88	.071	.079	.07	15195.56	48.06*

Note. *p < .05.

Table 7

Descriptive Statistics and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. GMA	26.33	4.01														
2. Videogame experience	0.00	0.83	0.08	(0.71)												
3. Openness	6.41	0.92	0.05	0.08	(0.86)											
4. Conscientiousness	6.11	0.93	0.00	0.05	0.36**	(0.87)										
5. Extraversion	5.54	1.07	−0.07	−0.06	0.42**	0.25**	(0.88)									
6. Agreeableness	6.82	0.93	−0.13*	0.05	0.31**	0.40**	0.37**	(0.90)								
7. Emotional stability	5.31	0.89	0.13*	0.10	−0.06	0.35**	0.16*	0.18**	(0.82)							
8. TEC int	4.05	0.47	0.11	0.06	0.35**	0.04	0.16*	−0.01	0.04	(0.69)						
9. TEC dep	3.26	0.68	0.08	0.07	0.28**	0.18**	0.04	0.06	0.09	0.38**	(0.73)					
10. SIDECS int emotion	3.15	0.87	0.09	0.17**	0.11	0.02	−0.12	0.09	0.12	0.15*	0.10	(0.92)				
11. SIDECS int cognition	3.17	0.93	0.05	0.10	0.11	0.02	−0.04	0.10	0.15*	0.10	0.16*	0.73**	(0.66)			
12. SIDECS dep emotion	2.95	0.71	0.07	0.05	−0.13*	−0.16*	−0.14*	0.02	−0.07	−0.05	0.10	0.36**	0.46**	(0.70)		
13. SIDECS dep cognition	3.05	0.73	0.01	0.16*	0.08	−0.01	−0.12	0.16*	0.12	0.06	0.17**	0.70**	0.68**	0.64**	(0.84)	
14. Performance	21.08	8.62	0.21**	0.47**	0.13*	0.10	−0.18**	0.07	0.11	0.07	0.05	0.41**	0.24**	0.00	0.27**	(0.95)

Note. Diagonal values are coefficient alpha reliabilities. GMA = general mental ability as reflected in self-reported ACT/SAT scores. TEC = trait epistemic curiosity. SIDECS = State Interest and Deprivation Epistemic Curiosity Scales. int = interest. dep = deprivation. N = 248. *$p < 0.05$, **$p < 0.01$, two−tailed.

Table 8

Coding Scheme of Change Variables in Discontinuous Growth Models

Variable	Pre-change period							Post-change period						
Measurement occasion (Session)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Skill acquisition (SA)	0	1	2	3	4	5	6	7	8	9	10	11	12	13
Transition adaptation (TA)	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Reacquisition adaptation (RA)	0	0	0	0	0	0	0	0	1	2	3	4	5	6
Quadratic skill acquisition (SA^2)	0	1	4	9	16	25	36	36	36	36	36	36	36	36
Quadratic reacquisition adaptation (RA^2)	0	0	0	0	0	0	0	0	1	4	9	16	25	36

Table 9

Discontinuous Growth Curve Model of Performance

	Model 1		Model 2		Model 3	
Variable	***B***	***SE***	***B***	***SE***	***B***	***SE***
Intercept	19.13**	0.66	19.13**	0.60	19.13**	0.60
Skill acquisition (SA)	4.02**	0.31	4.01**	0.31	4.02**	0.31
Transition adaptation (TA)	−14.43**	0.72	−14.28**	0.68	−14.28**	0.68
Reacquisition adaptation (RA)	−3.68**	0.43	−3.87**	0.32	−3.87**	0.32
Quadratic skill acquisition (SA^2)	−0.46**	0.05	−0.46**	0.05	−0.46**	0.05
Quadratic skill reacquisition (RA^2)	−0.03	0.05				
GMA			0.39**	0.10	0.38**	0.10
Videogame Experience			3.53**	0.49	3.54**	0.49
Openness			1.38*	0.53	1.31*	0.57
Conscientiousness			0.02	0.51	0.11	0.52
Extraversion			−1.56**	0.43	−1.61**	0.44
Agreeableness			0.62	0.50	0.67	0.50
Emotional Stability			0.33	0.50	0.31	0.51
Trait int					0.91	0.97
Trait dep					−0.57	0.65
AIC	24294.62		24217.02		24217.32	

Note. GMA = General Mental Ability. int = interest. dep = deprivation. **p* < 0.05, ***p* < 0.01

Table 10

Discontinuous Growth Curve Model of Performance

	Model 4		Model 5		Model 6	
Variable	***B***	***SE***	***B***	***SE***	***B***	***SE***
SIDECS int emotion	1.99*	0.75	0.83	0.97	1.40	1.05
SIDECS int cognition	−0.16	0.74	0.09	0.96	0.29	1.04
SIDECS dep emotion	−1.78*	0.77	−2.03*	0.97	−2.61*	1.05
SIDECS dep cognition	1.16	0.98	0.30	1.25	0.09	1.35
SA × int emotion			0.16	0.08	0.75**	0.20
SA × int cognition			−0.04	0.08	−0.26	0.20
SA × dep emotion			0.03	0.08	−0.21	0.20
SA × dep cognition			0.11	0.11	0.38	0.26
TA × int emotion					−4.72**	1.21
TA × int cognition					0.95	1.22
TA × dep emotion					2.65	1.19
TA × dep cognition					−1.27	1.54
RA × int emotion					−0.41	0.26
RA × int cognition					0.30	0.26
RA × dep emotion					0.05	0.25
RA × dep cognition					−0.35	0.33
AIC	24203.01		24207.12		24182.35	

Note. int = interest. dep = deprivation. *$p < 0.05$, **$p < 0.01$

Table 11

Summary of Item Characteristics for the Interest-Emotion Scale, α = .92 (95% CI .91, .94)

Item	*M*	*SD*	Item–scale total correlation	CFA factor loadings	*r*	LASSO *B*	Stepwise regression *B*
5. It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.	3.42	1.08	.77	.87	.42**	2.20	2.64
6. I would enjoy discussing Unreal Tournament with others.	3.08	1.18	.66	.82	.35**	0.48	1.26
9. New ideas about Unreal Tournament excite my imagination.	2.88	1.05	.70	.76	.24**	*nr*	*nr*
10. It is fun to discover new things about Unreal Tournament.	3.39	1.08	.83	.93	.36**	*nr*	*nr*
11. I enjoy trying new ideas for playing Unreal Tournament.	3.49	1.04	.77	.85	.34**	*nr*	*nr*
16. It is fascinating when I learn something new about Unreal Tournament.	3.12	1.08	.75	.84	.31**	0.26	*nr*
17. Unreal Tournament is intriguing to me.	2.91	1.16	.70	.89	.32**	0.52	*nr*
23. I feel inquisitive about Unreal Tournament.	2.94	0.97	.61	.71	.28**	*nr*	*nr*

Note. CFA = confirmatory factor analysis. *B*s and *r*s are in the prediction of performance scores averaged across all sessions. *nr* = not retained in the model. *$p < 0.05$, **$p < 0.01$

Table 12

Summary of Item Characteristics for the Interest-Cognition Scale, α = .66 (95% CI .58, .73)

Item Content	*M*	*SD*	Item–scale total correlation	CFA factor loadings	*r*	LASSO *B*	Stepwise regression *B*
2. When I learn something new about Unreal Tournament, I like to find out more about it.	3.43	1.02	.43	.70	.31**	1.62	2.58
12. I think about hypothetical situations in Unreal Tournament.	2.65	1.18	.47	.63	.10	*nr*	*nr*
21. I think about what might happen in Unreal Tournament if I try a new idea.	3.43	1.02	.51	.65	.17**	*nr*	*nr*

Note. CFA = confirmatory factor analysis. *B*s and *r*s are in the prediction of performance scores averaged across all sessions. *nr* = not retained in the model. *$p < 0.05$, **$p < 0.01$

Table 13

Summary of Item Characteristics for the Deprivation-Emotion Scale, α = .70 (95% CI .64, .75)

Item Content	*M*	*SD*	Item–total correlation	CFA factor loadings	*r*	LASSO *B*	Stepwise regression *B*
1. With Unreal Tournament, I feel restless without answers to the problems I have. (Problem–Solving)	2.83	1.09	.44	.52	–.06	*nr*	*nr*
3. It gets on my nerves when I'm close to understanding something in Unreal Tournament but can't quite figure it out. (Intolerance)	3.40	1.06	.55	.59	–.05	*nr*	*nr*
8. I will try to figure it out if something frustrates me about Unreal Tournament. (Intolerance)	3.56	1.00	.31	.59	.27**	1.36	2.63
13. It aggravates me if I can't remember something about Unreal Tournament. (Intolerance)	2.35	1.01	.47	.54	–.13*	–0.74	–1.67
18. I feel uncomfortable when I don't understand something about Unreal Tournament. (Competence)	2.62	1.15	.51	.70	–.02	*nr*	*nr*

Note. CFA = confirmatory factor analysis. *B*s and *r*s are in the prediction of performance scores averaged across all sessions. *nr* = not retained in the model. **p* < 0.05, ***p* < 0.01

Table 14

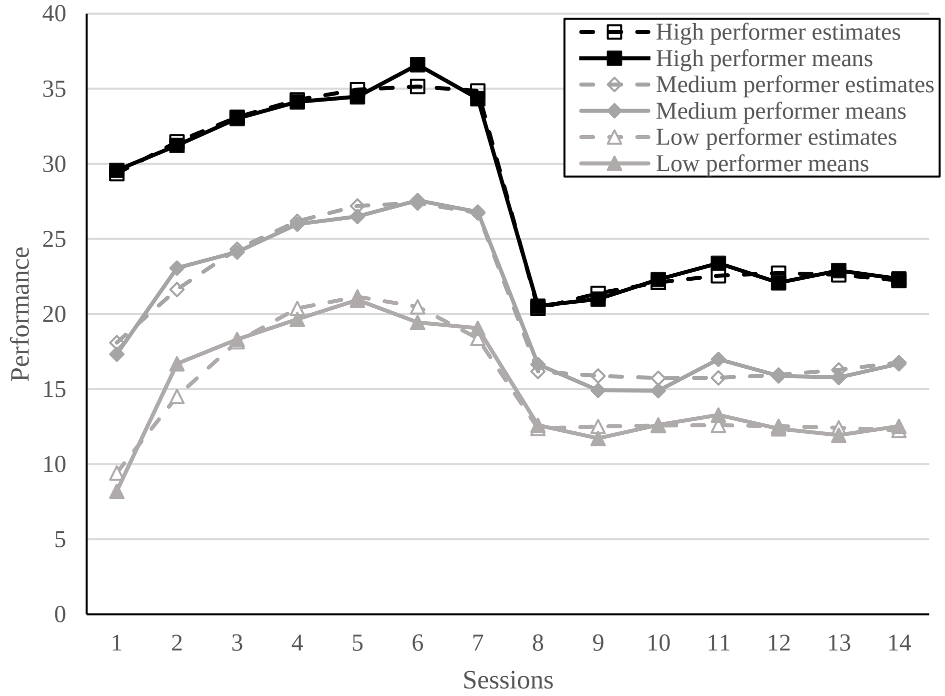
Summary of Item Characteristics for the Deprivation-Cognition Scale, α = .84 (95% CI .80, .87)

Item Content	*M*	*SD*	Item−total correlation	CFA factor loadings	*r*	LASSO *B*	Stepwise regression *B*
4. I can’t stop thinking about the challenges to playing Unreal Tournament. (Problem Solving)	2.74	1.08	.50	.61	.05	−0.58	*nr*
7. I work like a beast at aspects of Unreal Tournament that I feel must be solved. (Intolerance)	2.65	1.04	.60	.69	.24**	0.74	1.38
14. I’m critical of ideas and approaches to playing Unreal Tournament.(Intolerance)	2.94	0.99	.48	.50	.17**	0.47	*nr*
15. There are gaps in my understanding of Unreal Tournament that I want to fill. (Original)	3.46	1.07	.56	.69	.28**	1.49	1.82
19. When something puzzles me about Unreal Tournament, I think about it until I understand it. (Competence)	2.95	1.07	.62	.75	.23**	0.03	*nr*
20. I will keep trying hard until I fully understand Unreal Tournament. (Competence)	3.35	1.08	.61	.70	.26**	0.70	*nr*
22. I dwell about being able to play Unreal Tournament better. (Problem−solving)	2.79	1.13	.54	.67	.13*	*nr*	*nr*
24. I want answers for how to play Unreal Tournament better. (Naylor, 1981)	3.54	1.11	0.60	.72	.11	−0.33	*nr*

Note. CFA = confirmatory factor analysis. *B*s and *r*s are in the prediction of performance scores averaged across all sessions. *nr* = not retained in the model. *$p < 0.05$, **$p < 0.01$

Figure 1

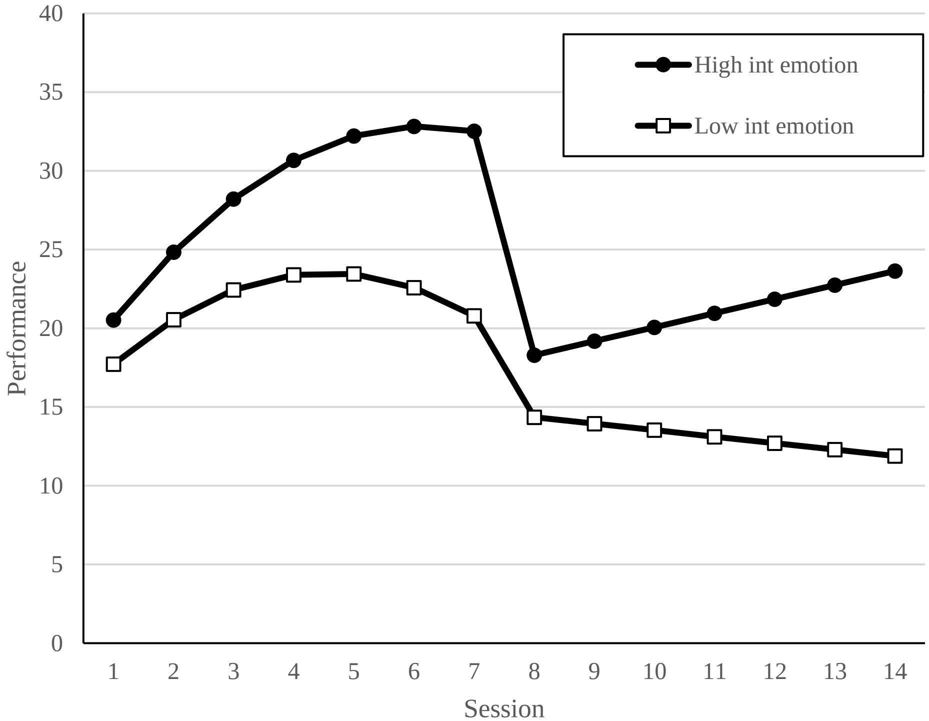
Performance Trend Across Sessions by Level of Performance



Note. Performance trend across sessions by Session 1 tertiles. Session 1-7 = pre-change. Sessions 8-14 = post-change. Performance scores could range from 0.00 to 1.00.

Figure 2

Estimated Effect of State Epistemic Curiosity Emotion Across Sessions



Note. int = interest. High/low state epistemic curiosity interest emotion = ±1 standard deviation.

Appendix A

SIDECS Interest Scale for Differing Contexts

UT2004	**Statistics**	**Excel**	**Tennis**
I enjoy trying new ideas for playing Unreal Tournament.	I enjoy trying new ideas when doing statistics.	I enjoy trying new ideas within Excel.	I enjoy trying new ideas when playing tennis.
It is fascinating when I learn something new about Unreal Tournament.	It is fascinating when I learn something new about statistics.	It is fascinating when I learn something new about Excel.	It is fascinating when I learn something new about tennis.
It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.	It is enjoyable to learn about aspects of statistics that are unfamiliar to me.	It is enjoyable to learn about aspects of Excel that are unfamiliar to me.	It is enjoyable to learn about aspects of tennis that are unfamiliar to me.
I would enjoy discussing Unreal Tournament with others.	I would enjoy discussing statistics with others.	I would enjoy discussing Excel with others.	I would enjoy discussing tennis with others.
When I learn something new about Unreal Tournament, I like to find out more about it.	When I learn something new about statistics, I like to find out more about it.	When I learn something new about Excel, I like to find out more about it.	When I learn something new about tennis, I like to find out more about it.
Unreal Tournament is intriguing to me.	Statistics is intriguing to me.	Excel is intriguing to me.	Tennis is intriguing to me.
I feel inquisitive about Unreal Tournament.	I feel inquisitive about statistics.	I feel inquisitive about Excel.	I feel inquisitive about tennis.
It is fun to discover new things about Unreal Tournament.	It is fun to discover new things about statistics.	It is fun to discover new things about Excel.	It is fun to discover new things about tennis.
New ideas about Unreal Tournament excite my imagination.	New ideas about statistics excite my imagination.	New ideas about Excel excite my imagination.	New ideas about tennis excite my imagination.
I think about hypothetical situations within Unreal Tournament.	I think about hypothetical situations within statistics.	I think about hypothetical situations within Excel.	I think about hypothetical situations within tennis.
I think about what might happen in Unreal Tournament if I try a new idea.	I think about what might happen in statistics if I try a new idea.	I think about what might happen in Excel if I try a new idea.	I think about what might happen in tennis if I try a new idea.

Appendix B

SIDECS Deprivation Scale for Differing Contexts

UT2004	Statistics	Excel	Tennis
With Unreal Tournament, I feel restless without answers to the problems I have.	With statistics, I feel restless without answers to the problems I have.	With Excel, I feel restless without answers to the problems I have.	With tennis, I feel restless without answers to the problems I have.
I dwell about being able to play Unreal Tournament better.	I dwell about being able to do statistics better.	I dwell about being able to use Excel better.	I dwell about being able to play tennis better.
I can’t stop thinking about the challenges to playing Unreal Tournament.	I can't stop thinking about the challenges to doing statistics.	I can't stop thinking about the challenges to using Excel.	I can't stop thinking about the challenges to playing tennis.
I will try to figure it out if something frustrates me about Unreal Tournament	I will try to figure it out if something frustrates me about statistics	I will try to figure it out if something frustrates me about Excel	I will try to figure it out if something frustrates me about tennis
I work like a beast at aspects of Unreal Tournament that I feel must be solved.	I work like a beast at aspects of statistics that I feel must be solved.	I work like a beast at aspects of Excel that I feel must be solved.	I work like a beast at aspects of tennis that I feel must be solved.
It is aggravating me that my ability to play Unreal Tournament 2004 is not better.	It is aggravating me that my ability to do statistics is not better.	It is aggravating me that my ability to use Excel is not better.	It is aggravating me that my ability to play tennis is not better.
It gets on my nerves when I’m close to understanding something in Unreal Tournament but can’t quite figure it out.	It gets on my nerves when I'm close to understanding something about statistics but can't quite figure it out.	It gets on my nerves when I'm close to understanding something about Excel but can't quite figure it out.	It gets on my nerves when I'm close to understanding something about tennis but can't quite figure it out.
I’m critical of my ideas and approaches within Unreal Tournament.	I'm critical of my ideas and approaches within statistics.	I'm critical of my ideas and approaches within Excel.	I'm critical of my ideas and approaches within tennis.
I want to keep learning until I fully understand Unreal Tournament.	I want to keep learning until I fully understand statistics.	I want to keep learning until I fully understand Excel.	I want to keep learning until I fully understand tennis.
When something puzzles me about Unreal Tournament, I think about it until I understand it.	When something puzzles me about statistics, I think about it until I understand it.	When something puzzles me about Excel, I think about it until I understand it.	When something puzzles me about tennis, I think about it until I understand it.
There are gaps in my understanding of Unreal Tournament that I want to fill.	There are gaps in my understanding of statistics that I want to fill.	There are gaps in my understanding of Excel that I want to fill.	There are gaps in my understanding of tennis that I want to fill.
I want answers for how to play Unreal Tournament better.	I want answers for how to do statistics better.	I want answers for how to use Excel better.	I want answers for how to play tennis better.