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FADING CURIOSITY: THE LONGITUDINAL TRAJECTORY OF STATE EPISTEMIC CURIOSITY AND THE ASSOCIATIONS WITH INFORMATION-KNOWLEDGE GAPS AND EXPLORATION IN COMPLEX SKILL LEARNING

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FADING CURIOSITY: THE LONGITUDINAL TRAJECTORY OF STATE EPISTEMIC CURIOSITY AND THE ASSOCIATIONS WITH INFORMATION-KNOWLEDGE GAPS AND EXPLORATION IN COMPLEX SKILL LEARNING

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Abstract

Fading curiosity results in missed opportunities for individuals, organizations, and educators in creativity, exploration, and performance. The primary purpose of my dissertation was to test fundamental assumptions about the longitudinal trajectory of state epistemic curiosity to provide a foundation for theoretical advancements and practical applications. Decreases in curiosity should occur as individuals progress through stages of learning, master complexity with task demands, and resolve gaps in understanding. The secondary purpose was to examine the within-person relationships between state epistemic curiosity and relevant time-varying variables, specifically information-knowledge gaps and task exploration. To accomplish these purposes, I used existing data from a laboratory study of 618 college students learning to perform a fast-paced, dynamic computer game that has been utilized in past research on complex skill learning with a surprise increase in task complexity (e.g., Hughes et al., 2013; Hardy et al., 2014, 2019b, 2024; Huck et al., 2020). Self-reports of state general curiosity as well as interest and deprivation aspects were measured with single-item scales. Results showed a decline in curiosity across skill acquisition (i.e., pre-change session scores), mixed results across transition adaptation (i.e., immediate post-change session scores), and a decrease across reacquisition adaptation (i.e., subsequent post-change session scores). Information-knowledge gaps and positive activating emotions were important predictors of curiosity at both the between- and within-person levels. State epistemic curiosity was an important predictor for exploration both at the between- and at the within-person levels. The results highlight the importance of continued research on fading curiosity in learning contexts.

Fading Curiosity: The Longitudinal Trajectory of State Epistemic Curiosity and the Associations with Information-knowledge Gaps and Exploration in Complex Skill Learning

Walt Disney once said, “We keep moving forward, opening new doors, and doing new things, because we're curious and curiosity keeps leading us down new paths” (The Walt Disney Archives, n.d.). What happens when a path becomes more familiar? We may ask fewer questions, look a little less earnestly, and begin to see the path as ordinary, desiring something new. This shift from novelty to boredom reflects a surprising concern: fading curiosity. Detachment at work is common with 85% of employees globally disengaging (Clifton, 2017). High school students are disconnecting with 66% stating they are bored at school every day (Caplan, 2014). Faded curiosity likely results in missed opportunities for greater creativity (Hardy et al., 2017), exploration (Berlyne, 1966), and performance (Rice, 2023). An important missing piece of the literature is the empirical evidence for how curiosity changes as learners develop knowledge and skill.

The primary purpose of my dissertation was to examine the theorized longitudinal decline of state epistemic curiosity, an important and untested claim discussed repeatedly in the literature. The insights from the present study provide a foundation for building theories and practical applications surrounding state epistemic curiosity. For theory, understanding the basic trajectory of state epistemic curiosity provides researchers with a starting place to further explore the mechanisms involved. The basic trajectory is also informative for developing practical interventions aimed at impacting state epistemic curiosity. The secondary purpose was to examine the relationships between state epistemic curiosity with theoretically relevant time-varying variables important for curiosity and learning. In doing this, I extend past theoretical insights with a new lens from Hardy et al.’s (2019a) Dynamic Exploration Exploitation Learning

(DEEL) model and Loewenstein's (1994) information-knowledge gap perspective. In reference to state epistemic curiosity, information-knowledge gaps are introduced as a key antecedent and exploration is introduced as a key outcome.

To accomplish these purposes, I used existing data from a laboratory study of 618 college students learning to perform a fast-paced, dynamic computer game that has been used in past research on complex skill learning (e.g., Hughes et al., 2013; Hardy et al., 2014, 2019b, 2024; Huck et al., 2020). The learning environment involved a task-change paradigm comprised of seven skill acquisition sessions followed by a surprise increase in task complexity and seven subsequent skill adaptation sessions. The surprise task change was introduced to expose information-knowledge gaps and spark curiosity. Each session consisted of two, 4-minute games and self-reports of state epistemic curiosity, information-knowledge gaps, and task exploration. Self-reports of state general curiosity as well as interest and deprivation aspects were measured with single-item scales. I examined hypotheses and research questions using hierarchical linear modeling with discontinuous growth curves that model changes in scores across periods of skill acquisition (i.e., pre-change session scores), transition adaptation (i.e., immediate post-change session scores), and reacquisition adaptation (i.e., subsequent post-change session scores). Each of the hypotheses and research questions for the present study are summarized in Table 1 along with a summary of the corresponding results.

The following section explains why epistemic curiosity matters, why longitudinal studies are needed, and how the construct has been measured. Afterwards, I explain my predictions on changes in curiosity scores across different periods of learning and the associations with information-knowledge gaps and exploration.

Background

The Importance of Epistemic Curiosity

Curiosity defined broadly is the “desire to know” (Merriam-Webster, n.d.). It has been studied with respect to perception (Collins et al., 2004), social relationships (Litman & Pezzo, 2007), the self (Litman et al., 2017), and information (Litman, 2008). The term, *epistemic curiosity* was initially coined by Berlyne (1954) to differentiate curiosity about information as opposed to perceptions and has been predominantly used in the literature since. Epistemic comes from the Greek term *episteme* meaning “knowledge” (Harper, n.d.).

In a dynamic and fast-paced world, novelty and complexity are increasing with technological advancements and progress in various academic and workplace contexts. For example, there is an ever increasing number of applications, statistical packages, research articles, courses, websites, videos, and images readily available on any subject via the internet. Artificial intelligence introduces an evolving realm of uncertainty. Additionally, learning and development are significant investments of time, resources, and effort on the part of individuals and organizations. In the United States, organizations spent $101.80 billion on training in 2023 (Training Magazine, 2023). In 2021, the United States Department of Education spent $260.45 billion (Prosperity for America, 2024). It is estimated that over 70% of adults engage in self-improvement regularly (Eser, 2025). The context of modern society places epistemic curiosity in a unique position as a psychological construct to advance theory regarding the increasing number of learning opportunities available and maximize their impact, for individuals, organizations, and educators.

In practice, organizations like Nike, Disney, Target, and Dell claim curiosity is important (Lievens et al., 2022). However, organizations similar to the ones listed may cultivate environments that limit curiosity with time pressures, rigid role structures, and few incentives to question or improve existing knowledge, thus ignoring fundamental needs for self-determination such as autonomy, competence, and relatedness (Baer & Oldham, 2006; Csikszentmihalyi, 2000; Deci & Ryan, 2000; Spreitzer, 1996). Beier et al. (2025) issued a call to industrial-organizational psychologists to address the more person-centered perspective of learning and skill development as opposed to an organizational level to better address lifelong learning and adaptability in future research. Building on this, Hardy (2025) urged industrial and organizational psychologists to look to curiosity for facing the uncertainties of global disruptions and technological advancements that are reshaping job demands.

An important motivational issue to industrial-organizational psychologists in particular has been a focus on the job satisfaction-performance relationship as a "holy grail" (Sender et al., 2020) with the assumption that "a happy worker is a productive worker" (Iaffaldano & Muchinsky, 1985, p. 269). The results on the topic have been inconclusive. Across cultures, happiness is generally defined as good luck, fortune, or favorable external conditions (Oishi et al., 2013). Good luck, fortune, and favorable external conditions can occur but may be elusive in today's dynamic work environment. Perhaps, industrial-organizational psychologists might modify this search instead to address engagement with the statement, "an engaged worker is a productive worker." Already, there is evidence for this with curiosity resulting in greater performance (Rice, 2023). Developing a basic understanding of epistemic curiosity would provide foundational support for the engagement-productivity worker relationship.

The Necessity of Longitudinal State Epistemic Curiosity Research

There are several reasons why epistemic curiosity should be studied longitudinally. First, epistemic curiosity was originally theorized to be a dynamic state with longitudinal changes (Berlyne, 1954). Second, research on state epistemic curiosity is better addressed at the within-person level as opposed to the between-person level. This is because learning and self-regulation are processes that occur at the within-person level (Hardy et al., 2019a). In this vein, it is important to note how prior research on self-efficacy (e.g., Vancouver et al., 2001), goal orientation (e.g., Yeo et al., 2009), and metacognition (Hardy et al., 2019b) has shown that relationships between self-regulation states and learning outcomes sometimes differ at the between-person and within-person levels. Changes can also occur over the course of learning. Only examining curiosity phenomena at the between-person level likely provides an incomplete and possibly misleading picture of epistemic curiosity as a dynamic state.

Third, practical applications of interventions aimed at impacting state epistemic curiosity longitudinally depend on initial assumptions about how the construct unfolds as knowledge and skill are developed. For example, in later sections of my dissertation, I describe my predictions about epistemic curiosity decreasing over the course of learning. Empirical evidence for the decline of epistemic curiosity provides the necessary backdrop for those attempting to intervene and sustain if not spark curiosity. Researchers should look to longitudinal empirical evidence as a foundation for understanding how curiosity can be helpful or necessary to improve creativity (Hardy et al., 2017), exploration (Berlyne, 1966), and performance (Rice, 2023).

Having longitudinal empirical evidence as a foundation would help bolster the validity of any conclusions made about the success or failure of interventions designed to impact state epistemic curiosity. As an example, a researcher might decide to apply Markey and Loewenstein's (2014) recommendations for increasing state epistemic curiosity by showing the importance of the task. This might be done by showing trainees how the skills developed in training relate to future employment opportunities (i.e., meaningfulness of the training content). The researcher could design a longitudinal study where the trajectory of state epistemic curiosity would be examined before and after such a meaningfulness intervention is administered. As another example of a training intervention, a discussion amongst experts of common areas of misunderstanding or lack of understanding could be used to expose information-knowledge gaps (Loewenstein, 1994). In such hypothetical examples, the data might show epistemic curiosity scores gradually decline before and after the intervention. A question could be posed to the researcher on whether the intervention was a success or a failure. It might be argued that the intervention was a success if state epistemic curiosity showed a discontinuous increase or less decline after the intervention. The intervention might be viewed as a failure without an increase or slower decline in state epistemic curiosity after the intervention.

Measurement of Epistemic Curiosity

There has been a lack of research attention on epistemic curiosity despite the importance of longitudinal research. Prior pursuits of longitudinal research on epistemic curiosity have been limited because there have been few validated scales for measuring the construct as a dynamic state which also addresses the important dimensionality emphasized in the literature. Scale development of curiosity has predominantly taken a trait-level approach (Wagstaff et al., 2020). Only one scale has recently been validated that measures the important dimensions identified in the literature on epistemic curiosity as a state. Specifically, Rice (2023) adapted previously validated trait scales to develop a new task-specific measure of state epistemic curiosity with separate scales for interest and deprivation.

Measuring the Interest and Deprivation Dimensions

Berlyne's (1966) initial studies addressing curiosity found two kinds of curiosity. One kind of curiosity referred to the need for greater complexity and pleasure. The other addressed the need to reduce uncertainty, such as when one is solving a problem. Building on the work of important advancements in measuring epistemic curiosity (Litman & Spielberger, 2003; Litman & Jimerson, 2004), Litman (2008) measured and differentiated these two different aspects of curiosity as enduring dispositions (i.e., traits). Litman brought clarity by recommending the following labels and definitions for the two different dimensions of curiosity: interest and deprivation. Interest is the "anticipated pleasure of new discoveries" (Litman, 2008, p. 1586). Deprivation is "reducing uncertainty and eliminating undesirable states of ignorance" (Litman, 2008, p. 1586). Litman's (2008) two-dimensional framework for epistemic curiosity has been the most frequently utilized conceptualization in psychological research (Yow et al., 2022).

The Need for a State Measure

The aforementioned contributions to the literature on epistemic curiosity primarily addressed the measurement of epistemic curiosity as an enduring disposition (i.e., trait) but left the measurement of dynamic within-person (i.e., state) changes unaddressed. Berlyne's (1954) original conceptualization of curiosity described epistemic curiosity primarily as a state. There were validation efforts to produce a viable state epistemic curiosity scale (e.g., Leherissey, 1971; Naylor, 1981; Boyle, 1983), but all took a unidimensional approach as opposed to Litman's (2008) interest-deprivation framework and Berlyne's (1966) original work.

Despite this, there were benefits of the state scale validation efforts, particularly with the work of Naylor (1981). Naylor (1981) showed differences in the trait and state distinction in curiosity via varimax rotation. The state items had factor loadings aligning with one factor and trait items had factor loadings with another factor. This brought initial evidence that state and trait epistemic curiosity should be measured separately. Naylor (1981) also provided better coverage of the interest dimension. In sampling different contexts, it was determined that there are general differences in state epistemic curiosity for different situations. However, the state scales only provided initial validation and the scale developers did not look at within-person variability.

The closest approximation to a longitudinal analysis is Naylor (1981) providing a test-retest reliability estimate of .59 over a 4-week period for the state scale. The state scale was administered to students after tests of verbal and numerical abilities and prior to when feedback was given 4 weeks later. The purpose of this was to show discriminant validity between the state and trait scales as well as showing correlations with the Strong Campbell Interest Inventory which measures realistic, investigative, artistic, social, enterprising, and conventional vocational interests. Interestingly, the state curiosity measure had the strongest association with investigative interests on both administrations, an area that is typically associated with curiosity and professions that are focused on problem solving (SAMPLE, 2008). Although Naylor (1981) provided important findings, the focus was not on mean differences or within-person variability across the two administrations.

Development of The State Interest and Deprivation Epistemic Curiosity Scales

Rice (2023) was the first to introduce a state epistemic curiosity scale, the State Interest and Deprivation Epistemic Curiosity Scales (SIDECS), that included both the interest and deprivation dimensions framed in the context of playing a complex computer game. Items were adapted from prior trait scales, Litman (2008) in particular, to capture the dynamic and transitionary moment-to-moment changes that might occur in a given task domain. The items were first subjected to a substantive content validation approach per Anderson and Gerbing (1991) such that a sample of students sorted the items into interest and deprivation definition after given definitions of each. All items were at or above the .50 C_{sv} recommended cut-off value by Anderson and Gerbing (1991), indicating support for the substantive content validity of the interest and deprivation scales.

Afterwards, 248 college males underwent training and practiced the complex video game. A confirmatory factor analysis revealed that a two-factor correlated model had better fit compared to a single-factor model and an uncorrelated two-factor model, closely meeting recommended cut-off values for fit statistics showing structural validity. Rice (2023) also introduced a post hoc alternative that divided the interest and deprivation dimensions into four areas; interest-emotion, interest-cognition, deprivation-emotion, and deprivation-cognition. This post hoc alternative showed better fit than the 2-factor model. Coefficient alpha scale reliabilities ranged from .66 to .92. Although the better fit showed evidence for emotion and cognition components, the strength of the some of the factor intercorrelations (e.g., interest-cognition and interest-emotion r = .73; interest-cognition and deprivation-emotion = r = .70) left uncertainty regarding the justification for bifurcating the interest and deprivation dimensions into cognition and emotion components.

Rice (2023) also examined predictive validity evidence for the SIDECS. First, the majority of the scales showed moderate correlations with performance. Correlations with performance were .00, .24, .27, and .41 for deprivation-emotion, interest-cognition, deprivation-cognition, and interest-emotion, respectively. Second, scores for the interest-emotion scale provided incremental validity in the prediction of skill-based performance beyond measures of general mental ability, past experience, Big Five personality dimensions, and trait epistemic curiosity. The results did not provide evidence of incremental validity for the other three dimensions, suggesting that interest-emotion curiosity is especially important to skill-based learning.

Predictions Regarding Changes in State Epistemic Curiosity

Despite persistent recognition that curiosity is important for learning, prior research has not examined how curiosity unfolds dynamically, particularly during skill acquisition and adaptation. As mentioned above, most prior research has examined curiosity with more of a stable, trait-based perspective. There is a lack of empirical evidence regarding changes in curiosity as knowledge and skill are developed. The present study addressed this gap by measuring state epistemic curiosity longitudinally in relation to information-knowledge gaps as a key theoretical antecedent and task exploration as a key theoretical outcome. The following sections discuss both general changes in learners and curiosity-related changes across skill acquisition, transition adaptation, and reacquisition adaptation.

Skill Acquisition

General Changes in Learners

During the learning process, learners interact with and respond to the task environment. There are generally three stages of skill acquisition described in the literature in terms of early, intermediate, and late learning (Ackerman, 1988; Kanfer & Ackerman, 1989; Fitts, 1964). Different terms have been used to describe early, intermediate, and later learning by Ackerman (1988), Anderson (1982), and Kanfer and Ackerman (1989). Early learning has been described as cognitive and declarative, intermediate learning has been described as associative and compilation, and late learning has been described primarily as procedural. Additionally, throughout skill acquisition, learners make decisions in terms of task exploration and skill refinement (Hardy et al., 2019a).

Early learning is primarily cognitive in nature as learners strive to understand basic task instructions and facts, with errors commonly occurring alongside gains in performance

(Anderson, 1982; Fitts, 1964; Fitts & Posner, 1967; Kanfer & Ackerman, 1989). Learners must choose among alternative approaches in developing knowledge and skill due to limited resources such as attention, time, and effort (Hardy et al., 2019a). Learners engage with a variable set of alternatives in their learning approach, providing breadth through exploration or depth through exploitation. The breadth is developed from exploring a wide range of knowledge components. Depth comes from exploiting and refining existing knowledge components.

In terms of an intermediate phase, information about the task is streamlined into a compilation, or chunking, of task components into a set of procedures (Gobet et al., 2001; Kanfer & Ackerman, 1989; Shea & Kovacs, 2013). Learning at this stage is described as associative in nature as learners are on the lookout for specific cues to improve the efficiency of their performance (Anderson, 1982; Fitts, 1964). Errors gradually decline during this phase as performance improves (Fitts & Posner, 1967). Learners also develop their learning approach in terms of exploring a wide variety of alternatives versus exploiting a single or small set of alternatives, or some blend of exploration and exploitation (Hardy et al., 2019a).

In the later phase, learning is described as automated as the performance of task components becomes more integrated and executed with little need for focused attention (i.e., controlled processing) (Kanfer & Ackerman, 1989; Fitts & Posner, 1967). The integration of components typically results in effective, durable, and efficient performance. Noticeable improvements are slight as increased effort comes with diminishing returns to performance (Fitts, 1964; Newell & Rosenbloom, 2013), although potential for generalization across a variety of task demands might increase (Arthur & Day, 2013). Despite the diminishing returns, expertise can be further developed through deliberate practice on areas seen as especially difficult and in need of improvement (Ericsson & Charness, 1994). Improvements at this point may also be termed proactive adaptation because learners continue to develop despite no changes in the learning environment (Ployhart & Bliese, 2006). As knowledge and skill are acquired, learners will ultimately differ in what was acquired. Learners may develop more breadth, more depth, or a balance of breadth and depth depending on how they allocated effort between exploration and exploitation over the course of learning (Hardy et al., 2019a).

Curiosity Changes in Learners

In the early stages of learning, learners become aware of information-knowledge gaps, which are critical for curiosity (Loewenstein, 1994; Hardy et al., 2019a). These information-knowledge gaps are associated with novelty, complexity, and uncertainty (Berlyne, 1950, 1954). Loewenstein (1994) defined information-knowledge gaps as the "discrepancy between what one knows and what one wishes to know" (Loewenstein, 1994, p. 93). Building on this, Hardy et al. (2019a) described information-knowledge gaps as "perceived discrepancies between what learners believe they currently know/can do (i.e., competence beliefs) and what learners want or need to know/be able to do (i.e., novelty motives)" (Hardy et al., 2019a, p. 202). Per Hardy et al.'s (2019a) DEEL model, the magnitude of the information-knowledge gaps signal the amount of resources (e.g., time, attention, and effort) needed to satisfy learners' novelty motives. Larger information-knowledge gaps signal that more resources are necessary. Smaller information-knowledge gaps signal that resources should be preserved or allocated to other goals.

During initial learning and as learners address information-knowledge gaps, questions may emerge about how the task is performed with rules and strategies for information-processing (Kanfer & Ackerman, 1989). The initial learning process is typically error prone (Kanfer & Ackerman, 1989) and learners are likely to be confused with violated expectations if assumptions are incorrect. Violated expectations are, "a discrepancy between what one perceives and what one expected to perceive" (Loewenstein, 1994, p. 93) and often leads learners to search for an explanation (Loewenstein, 1994). These situations can bring cognitive confusion and surprise (Berlyne, 1954).

As knowledge and skill are developed, learners experience several changes. Information-knowledge gaps are eventually resolved, reducing the prior uncertainty (Loewenstein, 1994). Knowledge is compiled and streamlined (Kanfer & Ackerman, 1989), reducing the cognitive confusion that occurs with errors and violated expectations. The perceived novelty and emotional impacts begin to wane (Berlyne, 1950). At first, task stimuli are alarming but this reaction diminishes with repeated exposure. Likewise, at first, learners are excited and curious but gradually acclimate to what was once intriguing. Learners are ready for greater complexity and growth once the given complexity is mastered (Dember & Earl, 1957). Curiosity likely declines when learners fail to see further complexity to master.

There are impacts of familiarity that extend beyond gaining skill. Learners have greater curiosity when there is a moderate level of familiarity (Berlyne, 1954). Berlyne (1954) framed this in terms of conflict. Conflict occurs when there is interference with prior learning that can be resolved by exploration and information-gathering. Too little familiarity occurs when there is not enough prior learning to arouse enough conflict. Too much familiarity occurs when the conflict is removed due to things going as expected. Repeated exposure to the task demands should result in greater amounts of familiarity, thereby decreasing the amount of learners' epistemic curiosity. Getting acclimated to task stimuli from repeated exposure is akin to notions of habituation. Habituation refers to the "behavioral response decrement that results from repeated stimulation and that does not involve sensory adaptation/sensory fatigue or motor fatigue" (Rankin et al., 2009, p. 136). Habituation can be useful in learning as learners filter out the irrelevant and focus on what is important.

Due to a combination of learning and repeated exposure to task stimuli, curiosity eventually fades without changes in task demands. This is because information-knowledge gaps are resolved, novelty decreases, complexity is mastered, familiarity increases, there are fewer instances of confusion and conflict, and learners become habituated to the task demands. Accordingly, the following hypothesis was tested.

> *Hypothesis 1:* State epistemic curiosity will decrease over the course of skill acquisition (across skill acquisition sessions).

With respect to the interest and deprivation dimensions, the longitudinal differences in the decline of the two dimensions have not been discussed in the literature nor has it been examined empirically. Without prior theory or empirical evidence, it is difficult to make a case for why either dimension should have greater or lesser decline. Both are likely to decrease. The interest dimension could decline faster due to the reduction in novelty and excitement with an increase in familiarity. The deprivation dimension could decline faster due to the reduction in uncertainty as information-knowledge gaps are filled, which is addressed as a research question in the present study. Additionally, similar research questions are also presented for transition adaptation and reacquisition adaptation regarding whether the interest or deprivation dimensions decrease or increase at a greater rate, following the hypothesized trajectory of state epistemic curiosity generally. Thus, I sought to answer the following research question.

> *Research Question 1*: Will interest or deprivation scores exhibit a greater decrease over the course of skill acquisition (across skill acquisition sessions)? That is, will there be a difference in the trajectory of scores over the course of skill acquisition between interest and deprivation curiosity?

Transition Adaptation

General Changes in Learners

Learners are directly impacted by changes to the learning environment. In the modern learning paradigm, learners are typically responsible for responding to unexpected disruptions (Hardy et al., 2024). This approach in the modern learning paradigm embraces active learning as opposed to learners being passive recipients (Bell & Kozlowski, 2008). In early research on training and development, there was an emphasis on limiting the control of learners via procedural training and developing routine expertise (Bell & Kozlowski, 2008). The approach of developing routine expertise becomes a liability when learners need to be flexible to constantly changing work environments. Disruptions in the modern workplace are common. Disruptions in task demands can stem from global events (e.g., COVID-19 and technological advancements), workplace events (e.g., downsizing and competition), and personal events (e.g., starting a new position and job crafting). Research on active learning provides the foundation for developing a better understanding of how learners adapt to changes (Bell & Kozlowski, 2008).

There are two different aspects of adaptive performance in a task-change paradigm: transition adaptation and reacquisition adaptation (Lang & Bliese, 2009). Transition adaptation refers to the immediate transfer of routines and expertise from a pre-change period to the changed task. Reacquisition adaptation addresses the full post-change period rather than immediately after the task change. Lang and Bliese (2009) first differentiated these different aspects of adaptive performance to isolate the role of general mental ability in individual performance after an unexpected task change. It is imperative that these different aspects of adaptive performance are isolated in the present study to show the changes in trajectory of curiosity alongside changes in curiosity's association with information-knowledge gaps and exploration. Both of these kinds of adaptive performance are reactive as learners adapt to changes in the environment (Ployhart & Bliese, 2006).

There are a number of general changes in learners when transition adaptation occurs. There is usually an immediate drop in performance, with the size of the decrease depending on learners' general mental ability. Prior to the transition, learners with higher general mental ability learn more about the task, experience performance gains, and have more to lose with proficiency once the task change occurs (Beier & Oswald, 2012; Lang & Bliese, 2009). Learners also experience decreases in positive emotions and increases in negative emotions (Jorgensen et al., 2021). Learners experience an increase in information-knowledge gaps and on-task effort with an increased shift towards learning-oriented effort (Hardy et al., 2024).

Curiosity Changes in Learners

Curiosity likely increases in the initial moments following a disruption in task demands. Assuming the disruption comes as a surprise, learners will have violated expectations and begin to search for an explanation (Loewenstein, 1994). New information-knowledge gaps are realized (Hardy et al., 2024), which are accompanied with novelty and uncertainty (Berlyne, 1950, 1954). Per Hardy et al.'s (2019a) DEEL, decisions with respect to balancing exploration and breadth versus exploitation and depth, begin again with an emphasis on exploration and breadth once there is a change in task demands, especially with increases in task complexity (Hardy et al., 2019a). With an unexpected change in task demands following a period of skill acquisition, learners seek to master complexity (Dember & Earl, 1957) and now have the opportunity to master new challenges (Lang & Bliese, 2009). As stated earlier, the present study utilizes a surprise change in task demands involving increased complexity. Accordingly, state epistemic curiosity should increase immediately following the surprise change in task demands. Thus, I examined the following hypothesis and research question.

> *Hypothesis 2:* State epistemic curiosity will increase during transition adaptation (in the first adaptation session after a change in task demands).

> *Research Question 2*: Will interest or deprivation scores exhibit a greater increase during transition adaptation (in the first adaptation session after a change in task demands)? That is, will there be a difference in score changes during transition adaptation between interest and deprivation curiosity?

Reacquisition Adaptation

General Changes in Learners

As stated previously, reacquisition adaptation addresses post-change performance beyond the immediate moments after the task change. During reacquisition adaptation, learners begin to recover from the immediate performance loss that occurred from the transition (Lang & Bliese, 2009). Learners perform systematic and analytical learning behaviors to understand the new challenges (Lang & Bliese, 2009). Learners also attempt to integrate novel information into their existing paradigms (Hardy et al., 2024).

It is likely learners become more cognizant of external and unstable causes to their performance (task difficulty and luck) when there is a surprise task changes that increases complexity (Jorgensen et al., 2021). There can be a tendency to give up somewhat as the task complexity increases and becomes too difficult for learners. Novices in particular do not have the sophisticated mental models that come with expertise and cannot formulate effective strategies as easily (Chi et al., 1981; Wilson et al., 2009). Depending on the expertise of the learner, information that is high in element interactivity (i.e., a large number of elements of information) requires a greater working memory load to process (Sweller, 2011). Additionally, complexity is associated with anxiety, which can tax cognitive resources (Hughes et al., 2013; Westlin et al., 2019). In short, even if learners decide to persist, novices require more extensive cognitive effort to complete difficult and complex tasks than experts (Chen et al., 2018).

The combination of emotions and self-evaluation may also play a role in learners giving up due to complexity in relation to learners' desired progress. Self-evaluation is "comparing one's progress to one's desired state or other standard" (Hughes et al., 2013, p. 83). The repeated self-evaluations may result in repeated negative emotions (e.g., frustrated, disappointed, discouraged), positive emotions (e.g., excitement and enthusiasm), and with violated expectations that prompt a search for an explanation. Repeated instances of negative self-evaluations would likely result in learners withdrawing from the task.

In reacquisition adaptation, learners with greater state epistemic curiosity show persistence via performance when complexity increases (Rice, 2023). State epistemic curiosity is a motivational state that can be useful when addressing complexity related obstacles. These obstacles may include lacking sophisticated mental models, the difficulty of formulating effective strategies, processing information that has high element interactivity, putting forth greater cognitive effort, regulating negative emotions, and resolving violated expectations.

Curiosity Changes in Learners

After the initial response to the surprise changes, learners experience the decline of curiosity again under the new task demands. Similar to the circumstances under skill acquisition, after repeated exposure, there will be a resolution of information-knowledge gaps, novelty decreases, complexity is mastered, familiarity increases, there are fewer instances of confusion and conflict, and learners again become habituated to the task demands. Therefore, I tested the following hypothesis and research question.

> *Hypothesis 3:* State epistemic curiosity will decrease over the course of reacquisition adaptation (across adaptation sessions).

> *Research Question 3*: Will interest or deprivation scores exhibit a greater decrease in scores over the course of reacquisition adaptation (across adaptation sessions)? That is, will there be a difference in the trajectory of scores over the course of reacquisition adaptation between interest and deprivation curiosity?

Predictions Regarding Within-Person Relationships with Time-varying Variables

The drive perspective to motivation is beneficial for understanding my predictions regarding the within-person relationships of state epistemic curiosity with relevant time-varying variables. Woodworth (1918) is credited as the first to describe "drive" (Steers & Porter, 1991). Although not explicitly mentioned, Woodworth (1918) explained the nuances of the stimulus-response relationship with respect to energy. The stimulus in and of itself has no power but the response lies in the organism and varies in the amount of energy that is expelled in response to basic needs like hunger or thirst. As an example, a rat that has been deprived of food for 8 hours runs faster for food than a rat that has been deprived for 4 hours. This describes a drive-reduction approach. Adding to this, Cannon (1939) described the concept of "homeostasis" in describing drive as a means for reducing the disequilibrium in the organism. For example, biological deficiencies result in hunger or thirst and the body does this to ensure there is an adequate supply of food and water. Hull (1943) is often credited with integrating drive as energy and habit as the relationship of past stimulus and response, with drive and energy resulting in the amount of effort produced by the organism.

Scholars debated whether the definition of drive should expand to include incentives. Hull (1943) and White (1959) differentiated between drive and incentives as different aspects of motivation, suggesting that drive was referring to the need and the incentive is what satisfies the need. Scheffield et al. (1954) suggested expanding the definition of drive to include a drive-induction perspective where organisms are primarily focused on incentives as the satisfiers.

These perspectives show a dual perspective with the desire to (a) reduce the unpleasantness of the need (i.e., drive-reduction) and (b) approach the pleasure of the incentives to satisfy the need (i.e., drive-induction).

The drive perspective is referenced at times in more modern research, with Bandhu et al., (2024) as an example, but the frequency and use of the perspective has waned over the years. Researchers, such as White (1959), questioned the drive perspective and concluded that drive theory was inadequate when trying to explain psychological constructs (e.g., exploration, competence, achievement) due to origins in biological needs (e.g., hunger, thirst, sex). Criticisms of drive theory continued with Neiss (1988) finding contradictory evidence for drive with motor performance. However, drive theory has been helpful in explaining the reduction and approach of psychological constructs such as in the stress-performance relationship (Staal, 2004).

The drive perspective mirrors the deprivation and interest dimensions of epistemic curiosity. Deprivation reflects the need to reduce unpleasant states similar to the drive-reduction perspective. Interest reflects the approach of possible discoveries similar to the drive-induction perspective. Information-knowledge gaps in particular are relevant to the aversive states of ignorance and are presented in a similar manner to drive-reduction theory in that greater information-knowledge gaps result in greater curiosity. The present study also addressed arguments made by White (1959) in trying to explain exploration in terms of reducing aversive states (i.e., deprivation) and approaching incentives (i.e., interest) with curiosity. This aspect of my dissertation was exploratory in that it addressed an unclear picture of whether exploration better relates to satisfying a need (i.e., deprivation) or approaching novelty (i.e., interest).

Information-knowledge Gaps as an Antecedent

The likely relationship between information-knowledge gaps and curiosity has been discussed in the literature since Loewenstein's (1994) review but has not been empirically examined. The information-knowledge gap perspective positions curiosity as a reference-point phenomenon between what is currently known and what learners want to know. Similarly, Berlyne (1954) has asserted that curiosity is a drive needing to be reduced (i.e., satisfied). Including information-knowledge gaps as a time-varying variable allows for an empirical examination of the long-held notion that information-knowledge gaps are strongly and positively associated with epistemic curiosity. A reduction in information-knowledge gaps is the primary but untested explanation for why curiosity decreases over the course of learning and can be examined at the within-person level. An inference can also be made that learners with greater information-knowledge gaps will have greater state epistemic curiosity scores and can be examined at the between-person level. This would indicate that the perception of information-knowledge gaps is important in predicting who might have greater state epistemic curiosity and engagement with learning new tasks. Therefore, I tested the hypotheses that there is a positive relationship between information-knowledge gaps and state epistemic curiosity at both the within- and between-person levels.

> *Hypothesis 4:* At the within-person level, there will be a positive relationship between information-knowledge gaps and state epistemic curiosity.

> *Hypothesis 5:* At the between-person level, there will be a positive relationship between information-knowledge gaps and state epistemic curiosity.

The origin of the deprivation dimension stems from Loewenstein (1994) suggesting that the perception of an information-knowledge gap results in cognitively induced deprivation, which is unpleasant to learners. When looking to resolve information-knowledge gaps, learners seek to mitigate the unpleasantness of deprivation. The interest dimension primarily addresses anticipated pleasure and is less likely associated with information-knowledge gaps than the unpleasant states associated with deprivation. Therefore, the following hypothesis was tested.

> *Hypothesis 6:* At the within-person level, the positive association between deprivation curiosity and information-knowledge gaps will be stronger than the association between interest curiosity and information-knowledge gaps.

Exploration as an Outcome

There is a foundational assumption that exploration is strongly associated with curiosity. The association dates back to Berlyne's (1950) seminal work, which proposed that curiosity is an important motivation for exploration, going as far as to say it is a "determinant" of exploratory behavior. Berlyne later revisited this point on multiple occasions and distinguished two different kinds of exploration in terms of general (i.e., diversive) and specific (Berlyne, 1954, 1955, 1966). The development of trait scales diverged into two different directions in capturing the diversive-specific distinction in exploration. Litman (2008) included the affective component and these developed into the interest-deprivation distinction for curiosity. Kashdan et al. (2004) reframed general exploration to a broad exploration dimension and specific exploration to an absorption dimension. Both provided empirical evidence for the structural validity of their claims, although the interest-deprivation distinction reflected in Litman (2008) is used much more frequently in the literature (Yow et al., 2022). Both of these approaches favor the integration of exploration in the measurement of curiosity, which highlights how closely related these two constructs are.

Hardy et al.'s (2019a) DEEL model of self-regulated learning integrated principles from curiosity theory describing the role of exploration in learners' decision-making process as they navigate and perform in complex learning environments. Hardy et al. (2019a) proposed that information-knowledge gaps are the mechanism for guiding effort allocation decisions towards learning something new (exploration) versus maximizing immediate performance benefits (exploitation). Hardy et al. (2024) provided evidence for this proposition by showing a decreased emphasis on exploration-related behaviors as information-knowledge gaps shrank. Exploration-related behaviors increased with an expanded information-knowledge gap after a novel change in task demands.

There have been a few approaches for defining exploration. Berlyne (1950) defined exploration as when “an organism will learn to respond to a curiosity-arousing stimulus with activity which will increase stimulation by it” (Berlyne, 1950, p. 74). Kashdan et al. (2004) defined exploration as “general appetitive strivings for novelty and challenge irrespective of source” (Kashdan et al., 2004, p. 296). Hardy et al. (2019a) defined exploration as “process-level learning strategies, cognitions, and behaviors that emphasize engaging a wide variety of alternatives (e.g., task strategies, training material, opportunities for development) with little focus on identifying a single or limited set of preferred alternatives” (Hardy et al., 2019a, p. 202). These perspectives are similar in how they propose a positive interplay between state curiosity, exploratory behavior, and learning. Exploration has been viewed as a response to stimulation (Berlyne, 1950), an appetitive striving for novelty and challenge (Kashdan et al., 2004), and as an adaptive learning approach (Hardy et al., 2019a). These perspectives are aligned in their assertion that curiosity is closely associated with exploration.

Therefore, I tested the hypotheses that there is a positive relationship between state epistemic curiosity and exploration at both the within- and between-person levels. The within-person association suggests that when state epistemic curiosity increases, exploration also increases. The between-person association suggests that learners with greater state epistemic curiosity scores explore their task environments more than those with less curiosity.

Hypothesis 7: At the within-person level, there will be a positive relationship between state epistemic curiosity and exploration.

Hypothesis 8: At the between-person level, there will be a positive relationship between state epistemic curiosity and exploration.

Although the interest and deprivation dimensionality are both likely to be positively associated with exploration, differences between the dimensions are also likely. The interest dimension typically addresses the approach of novelty (Berlyne, 1950). The deprivation dimension primarily addresses reducing uncertainty (Loewenstein, 1994). The present research adds to the theoretical discussion in addressing whether exploration better addresses the approach of novelty or the reduction in uncertainty. Therefore, the following research question was examined.

Research Question 4: Will the association between interest and exploration be stronger or weaker than the association between deprivation and exploration at the within-person level?

Method

Development of Interest and Deprivation Single-item Scales

Short scales are useful for longitudinal designs where repeated measures are frequently utilized. As was previously described, Rice (2023) was the first to provide an interest and deprivation state epistemic curiosity scale, which is important for the purposes of the present study. In contexts where there is a need for frequent and repeated measurements of epistemic curiosity, the full 24-item scale may become unnecessarily burdensome to participants. As an example, four administrations of the 24-item version of the SIDECS would require participants to complete 96 items in total whereas four administrations of a 5-item version covering similar information would only require the completion of 20 items in total. The full 24-item version may impose unnecessary burden in longitudinal contexts when similar information can be captured using fewer items.

In the development of the SIDECS, Rice (2023) adapted items from Litman (2008) and included items from Litman and Jimerson (2004) and Litman and Spielberger (2003). The inclusion of these additional items may partly account for why the CFA fit indices did not reach the same cutoffs observed for the 10-item trait scale reported by Litman (2008). Importantly, Rice (2023) demonstrated that the key distinction between the interest and deprivation dimensions was retained despite the broader item set. Litman's (2008) trait epistemic curiosity scale included the 10 items that were most representative of the interest and deprivation dimensions, dropping items that were not as representative. Additionally, Rice (2023) provided substantive content validation evidence that supported Litman's (2008) earlier findings with these items differentiating the interest and deprivation dimensions.

The 10-item scale may still be unnecessarily burdensome to participants in intensive longitudinal contexts. Single-item scales offer a practical approach for contexts involving repeated-measures designs testing theoretical claims. Single-item scales have the potential to perform equally well to short measures in covering content (Elo et al., 2003), showing convergent and discriminant validity (Fisher et al., 2016), and in the prediction of criterion (Diamantopoulos et al., 2012). Although there may be concerns that single-item scales are unreliable, single-item reliability can be calculated using the Spearman-Brown prophecy formula (Fuchs & Diamantopoulos, 2009; Wanous et al., 1997) with frequently used single-item scales showing alpha estimates from .14 to .68 (Postmes et al., 2013).

Rice (2023) was cognizant of the necessity for short scale development and provided item psychometric properties for individual state epistemic curiosity items for single-item scale use. Rice (2023) provided item properties for each of the 24-items in how they were representative of the different scales (i.e., item-scale correlations and CFA factor loadings) and predicted task performance (i.e., correlations and stepwise regression). Using a re-analysis from Rice (2023), the 10 items for Litman (2008) were reviewed based on the same criteria to determine single items that were representative of the different scales and predicted task performance (see Table 2). In the present study, Item 4 (i.e., "It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.") was used to operationalize interest curiosity. Of all the interest items, Item 4 yielded the strongest zero-order correlation with performance and largest stepwise regression weight ($r = .44$, $\beta = .34$, ps $< .001$). The item-total scale correlation was .76 and its factor loading was .89. Item 4's Spearman-Brown alpha was .57. Item 7 (i.e., "I will try to figure it out if something frustrates me about Unreal Tournament.") was used to operationalize deprivation curiosity. Of all the deprivation items, Item 7 yielded the strongest zero-order correlation with performance and the largest stepwise regression weight ($r = .30$, $\beta = .20$, ps $< .001$). The item-total scale correlation was .49 and its factor loading was .70. Item 7's Spearman-Brown alpha was .33.

Participants

The final sample includes 618 undergraduate students at a public southwestern university who participated in exchange for research credit. Participants were omitted from the final sample for attrition ($n = 65$), computer errors ($n = 25$), and flatlining repeatedly on performance measures ($n = 14$). Participants omitted due to attrition included participants with unusually lengthy survey completion times that prevented study completion within the 4-hour study window ($n = 23$), those who withdrew saying they were not feeling well ($n = 6$), and requests for partial research credit following partial study completion ($n = 5$). Reported ages ranged from 18 to 36 ($M = 19.11$, $SD = 1.81$) with 323 participants identifying as male (52%) and 295 participants as female (48%). Reported ethnicity includes 343 as Caucasian (55.5%), 44 as

Black/African American (7.1%), 71 as Hispanic/Latino (11.5%), 19 as Native American (3.1%), 44 as Asian (7.1%), 67 as multiple (two or more ethnicities; 10.8%), and 19 as other (3.1%). For variables with missing values (<1% across all variables), mean imputation was applied.

Performance Task

Unreal Tournament 2004 (UT2004), a science fiction first-person shooter computer game, was utilized for the criterion task. Developed by Epic Games (2004), UT2004 is complex and has been used in past research on self-regulation and complex skill learning (Hardy et al., 2014; Hardy et al., 2019a). The objective was to destroy enemy opponents and avoid being destroyed. Every time the avatar and enemy opponents are destroyed, they reappeared at another location on the map. This continues for 4 minutes of gameplay. At the end of each game, the participant is provided performance related feedback.

The enemy opponents are computer-controlled bots. Scattered across the arena are pick-ups including weapons, health enhancements, power-ups that can enhance abilities for a short duration, and collectibles that result in greater enhancements (e.g., invisibility, increased movement, rapid firing capacity, and gradual health increases). There are advantages and disadvantages for each weapon, including primary and alternate fire, which requires knowledge of the different capabilities and appropriate uses for successful handling. Power-ups include increased damage per shot and extra protection. The greater enhancements require specific combinations of button presses after gathering a certain number of collectibles.

Procedure

Participants were informed that the study's purpose was to investigate how individuals learn a complex and dynamic video game. Participants first completed a virtual consent form at an individual cubicle computer station. Then participants were given questionnaires focusing on demographics, past video game experience, and trait epistemic curiosity alongside several other measures not relevant to the purposes of the present study. The participants were encouraged to have high performance through a drawing to win one of five $25 gift cards. Participants could enter the drawing for every trial in which their performance score falls within the top 50% of all single game performance scores. To help the participants know the controls, weapons, resources, and objectives while playing UT2004, a 15-min. training video was presented alongside a sheet outlining the information covered in the training presentation. A 1-minute practice trial with no computer-controlled opponents was provided to participants to support learning the controls.

Each individual trial lasted 4 minutes with 28 trials in total. After the completion of two trials, also known as a session, self-reports of exploration, exploitation, emotions, information-knowledge gaps, and state epistemic curiosity were given. These self-reports were given at 14 consistent intervals for the duration of the study, with slight variation when breaks were given to participants.

The computer-controlled bots in UT2004 have a difficulty scale from 0-7 with 0 as the easiest to defeat and 7 as the most difficult. For the duration of the study, the computer-controlled opponents were set to the difficulty of “5”. The initial map was a small canyon fortress with canyon walls creating a surrounding barrier. Without warning, and halfway through the protocol after Trial 14, the map was changed and the number of enemies increased from two to nine. The newer map was an oil rig with no surrounding barriers. The absence of barriers allowed the participants’ avatar and enemy opponents to fall from the platform.

Altogether, the learning environment involved a task-change paradigm comprised of seven skill acquisition sessions followed by a surprise increase in task complexity and seven subsequent skill adaptation sessions. Each session consisted of two 4-minute games and self-reports of state epistemic curiosity, information-knowledge gaps, and exploration. At Session 7, just before the task change, and after Session 14, at the end of the study, participants completed additional self-report measures, including additional state epistemic curiosity items. These additional state epistemic curiosity items were part of a scale development effort not germane to the purpose of my dissertation.

Measures

Information-Knowledge Gaps

The magnitude of information-knowledge gaps was operationalized with Hardy et al.'s (2024) measure that covers four different aspects: the map, weapons, strategies and the task generally. Responses were a percentage and ranged from 0 to 100 with the prompt for each statement stating, "remains to be discovered, tried, and understood." An example item is, "What percentage of the weapons and approaches to using weapons in Unreal Tournament remains to be discovered, tried, and understood?" The alpha reliability for this scale has previously ranged from .87 to .94 (Hardy et al., 2024).

State Epistemic Curiosity

A single general state epistemic curiosity item was used for Hypotheses 1-5, 7, and 8, which are agnostic to specific dimensions of curiosity: "How curious are you about Unreal Tournament?" Responses to this item were on a 9-point Likert scale (1 = *Very slight/not at all*, 3 = *A little*, 5 = *Moderately*, 7 = *Quite a bit*, 9 = *Extremely*). For Hypothesis 6 and all the research questions, which concern interest and deprivation dimensions of curiosity, the aforementioned single items for interest (Item 4) and deprivation (Item 7) were used. Responses to these items were on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*).

Exploration

Exploration was operationalized with Hardy et al.'s (2024) composition of on-task learning effort allocated toward exploration versus exploitation. One exploration item and one exploitation item were used in the calculation of this composition score. The exploration item is, "How hard did you try to learn something new in the previous game?" The exploitation item is, "How hard did you try to perform well during the previous game?" Responses to these two items are on a 10-point Likert scale (0 = *Not at all*, 10 = *Extremely hard*). The exploration composition score is calculated as the exploration score divided by the sum of the exploration and exploitation scores. Hardy et al. (2024) used the terms learning effort and achievement effort synonymously for exploration and exploitation, respectively.

Control Variables

Self-reported sex, videogame experience, general mental ability (GMA), trait epistemic curiosity, and state emotions were used as control variables. Four items were used to measure videogame experience similar to prior studies on complex skill learning using UT2004 (e.g., Hardy et al., 2019b; Richels et al., 2020; Hughes et al., 2013). The first item addresses how often participants played videogames in general over the past 12 months with a 5-point Likert scale response (1 = *Not at all*, 5 = *Daily*) with a follow-up question asking how many hours per week participants typically play videogames. Two other items concern first-person shooter games specifically using the same response scales: "Over the last 12 months, how frequently have you typically played first-person shooter video/computer games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament, etc.)?" and "How many hours per week do you typically play first-person shooter games?" Items with the same response scale are averaged and then standardized, and then the two standardized pair of items are averaged into a single composite score. The reliability of this videogame experience measure has estimates from .72 to .86 (Hardy et al., 2014; Hughes et al., 2013; Richels et al., 2020). Self-reports of American College Testing (ACT) and Scholastic Aptitude Test (SAT) were used to operationalize GMA.

Trait epistemic curiosity was measured using the five interest and five deprivation items from Litman (2008). Responses to these scales were completed with a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). An example interest item is, "When I learn something new, I like to find out more about it." An example deprivation item is, "I get frustrated if I can't figure out a problem, so I work harder." Prior estimates of alpha reliability for the interest scale are .69 (Rice, 2023) and .82 (Litman, 2008). Prior estimates of alpha reliability for the deprivation scale are .73 (Rice, 2023) and .76 (Litman, 2008).

State emotions were measured using Watson's (1988) Positive Affect Negative Affect Schedule (PANAS). The items were adapted and participants were asked to rate the extent they experienced an emotion during the past two games with a 9-point Likert scale (1 = *Very slight/not at all*, 9 = *Extremely*). Positive activating emotions included "enthusiastic", "happy", and "excited". Negative activating emotions consisted of the emotions "angry", "anxious", "frustrated", "irritated", "tense", and "uneasy". Jorgensen et al.'s (2021) estimates of alpha show reasonable reliability for both positive activating emotions (.85) and negative activating emotions (.86). Only the activating emotions were included due to prior theory espousing curiosity as an activated motivational state (Berlyne, 1954).

Task performance was measured but is not included in the discontinuous mixed-effects growth models due to the variable not being central to the purposes of the present study. Performance on Unreal Tournament 2004 is calculated using a composite consisting of kills, deaths, and rank during the task similar to Hardy et al. (2014) with an alpha reliability of .84 (Jorgensen et al., 2021).

Results

Descriptive statistics, intraclass correlations (ICCs), reliabilities, and within- and between-person correlations are presented in Table 3. The ICC indicated that the proportion of variance attributable to between-person differences was above .50 for most variables with the exception of exploration, which showed greater within-person variance (ICC = .40). The correlations among the curiosity scores—general, interest, and deprivation—were strong at both the between-person level (r = .70 to .83) and at the within-person level (r = .61 to .73), and these items were similar in their correlations with the other variables in the study at both the between- and within-person levels. For example, the associations of the curiosity scores with exploration were similar to one another at the between-person level (r = .32 to .36) and at the within-person level (r = .29 to .33). Additionally, state interest and state deprivation did not show strong differences with their trait counterparts (state interest with trait interest $r = .22$, $p < .001$; state interest with trait deprivation $r = .17$, $p < .001$; state deprivation with trait deprivation $r = .23$, $p < .001$; state deprivation with trait interest $r = .26$, $p < .001$).

Figure 1 displays the means for the repeated measures across all sessions. In general, and as expected, most of the variable scores declined over the course of skill acquisition and reacquisition adaptation, with performance as the only exception (see Panel H). The trends of performance, emotions, information-knowledge gaps, and exploration were consistent with past research on complex skill learning generally and for this task specifically (Hardy et al., 2024; Jorgensen et al., 2021; Richels et al., 2020). Surprisingly, state interest (see Panel F) and state deprivation (see Panel G) had a slight increase in scores before the task change (i.e., measurement occasion, Session 7) and at the end of the study (i.e., measurement occasion, Session 14). A possible reason for the increases may in part be due to the inclusion of the other state curiosity items (part of a scale development effort not germane to my dissertation) at those specific times alongside the interest and deprivation measures used for my dissertation.

Discontinuous mixed-effects growth models were used to examine state epistemic curiosity and exploration during skill acquisition (SA), transition adaptation (TA), and reacquisition adaptation (RA), similar to Jorgensen et al. (2021). Table 4 displays the coding scheme from Bliese and Lang (2016) used in the present study. Skill acquisition is the linear rate of the outcome variable (i.e., state epistemic curiosity and exploration) change in the pre-change period. Transition adaptation is the expected outcome variable change following the task change. Reacquisition adaptation is the linear rate of change in the outcome during the post-change period. Quadratic trends, quadratic acquisition (SA^2) and reacquisition (RA^2), were used to account for curvilinear change in the pre- and post-change periods. A series of models were tested following Bliese and Lang (2016) separately for general state epistemic curiosity (see Table 5), interest curiosity (see Table 6), deprivation curiosity (see Table 7), and exploration (see Tables 8 and 9) to address the hypotheses and research questions.

For all outcome variables, Step 1 included the basic growth model including SA, TA, RA, SA^2, and RA^2. Step 2 included the control variables of sex, GMA, videogame experience, and trait interest and deprivation curiosity. This step also included positive activating emotions and negative activating emotions at both the between- and within-person levels. Step 3 included the antecedent measure at both the between- and within-person levels for all models. For the analyses with exploration as an outcome variable, the repeated measures (i.e., emotions and curiosity) were specified as cross-lagged because exploration was measured prior to the other repeated measures. In other words, emotion and curiosity measures at Session 1 predicted exploration at Session 2, emotion and curiosity at Session 2 predicted exploration at Session 3, etc. (see Table 4).

Additional analyses were also conducted as robustness checks of the effects observed in testing the substantive hypotheses and research questions. For the sake of parsimony, all the details for these analyses are not presented because none of the conclusions regarding the tests of the hypotheses and research questions differed based on these additional analyses. For example, the interactions of all variables with the growth trends (SA, TA, and RA) were tested and largely nonsignificant. The impacts of emotions on the results for curiosity and exploration were also tested by removing their effects from the final model. The standardized coefficients were virtually identical after removing emotions from the models. The analyses with state interest and state deprivation as outcomes were also performed again with the removal of the scores for Sessions 7 and 14 due to the aforementioned slight increase in scores prior to the task change (dummy coding for the growth variables were altered accordingly). In particular, these additional analyses were important to testing Hypothesis 2 and Research Questions 2a and 2b concerning increases in curiosity scores at transition adaptation. Ultimately, removing the Session 7 and 14 scores did not change the substantive effects, and thus conclusions did not change.

Changes in State Epistemic Curiosity

Skill Acquisition

Hypothesis 1 predicted that state epistemic curiosity would decline over the course of skill acquisition. The Model 1 results in Table 5 support this hypothesis in the expected direction for general state epistemic curiosity during skill acquisition (SA $\beta = -.331$, $p < .001$, 95% CI [–.408, –.253]). The significant quadratic trend (SA^2 $\beta = .207$, $p < .001$, 95% CI [.125, .288]) suggested that the non-linear decrease slowed over the course of skill acquisition. Similar findings were found for both interest and deprivation (see Tables 6 and 7). These findings support a decline in state epistemic curiosity during skill acquisition.

Research Question 1 addressed whether interest or deprivation would decline at a faster rate over the course of skill acquisition (see Model 1 in Tables 6 and 7). The effects showed a greater decrease during skill acquisition for deprivation (SA $\beta = -.603$, $p < .001$, 95% CI [–.712, –.495]) than for interest (SA $\beta = -.408$, $p < .001$, 95% CI [–.509, –.306]). There was a small overlap in the confidence intervals. When confidence intervals overlap, Paternoster et al. (1998) recommended conducting a difference test using the unstandardized coefficients and the standard errors for the two effects. This was done with interest ($B = -.371$, $SE = .047$) and deprivation ($B = -.554$, $SE = .051$), and the difference was significant ($Z = 2.64$, $p = .008$). Thus, the results show that deprivation scores declined at a faster rate over the course of skill acquisition than the interest scores.

Transition Adaptation

Hypothesis 2 predicted that state epistemic curiosity would increase during transition adaptation. The Model 1 results in Table 5 support this hypothesis for general state epistemic curiosity (TA $\beta = .054$, $p < .001$, 95% CI [.033, .075]). However, as described below, the TA main effects for interest and deprivation curiosity were not positive and statistically significant (see Tables 6 and 7). Thus, the results show mixed support for the notion that state epistemic curiosity increases during transition adaptation.

Research Question 2 addressed whether interest or deprivation would increase more during transition adaptation as shown in Tables 6 and 7. Contrary to expectations, the Model 1 TA main effects were not positive for either deprivation or interest curiosity. In fact, the results for deprivation showed a significant decrease during transition adaptation (TA β = –.036, $p < .001$, 95% CI [–.062, –.010]). The effect for interest curiosity was also negative, but it was not statistically significant (TA β = –.018, $p = .189$, 95% CI [–.044, .009]). A difference test was performed again on the unstandardized estimates and standard errors for interest ($B = –.043$, $SE = .033$) and deprivation ($B = –.091$, $SE = .033$), but the difference was not significant ($Z = 1.03$, $p = .300$). These findings do not provide clear evidence of a difference between interest and deprivation in the rate of change over the course of transition adaptation.

As mentioned above, results for the additional analyses that involved the removal of Session 7 and 14 scores, did not substantively change conclusions for interest curiosity. The main effect was not positive as expected nor was the effect statistically significant (Model 1 TA β = .011, $p = .424$, 95% CI [–.016, .037]). For deprivation, the results again did not show a statistically significant positive effect, but in contrast to the original analyses the effect was no longer negative or statistically significant (Model 1 TA β = .005, $p = .722$, 95% CI [–.021, .030]). Altogether, with respect to transition adaptation, the results show scores in interest and deprivation do not increase during transition adaptation.

Reacquisition Adaptation

Hypothesis 3 predicted that state epistemic curiosity would decline over the course of reacquisition adaptation. The Model 1 results in Table 5 support this hypothesis for general state epistemic curiosity decreasing during reacquisition adaptation (RA β = –.389, $p < .001$, 95% CI [–.433, –.345]). The significant quadratic trend (RA^2 β = .205, $p < .001$, 95% CI [.169, .240]) suggested the nonlinear decrease slowed over the course of reacquisition adaptation. Similar findings were observed for interest and deprivation (see Tables 6 and 7). Together, these findings show a decline in state epistemic curiosity during reacquisition adaptation.

Research Question 3 addressed whether interest or deprivation would decrease at a faster rate over the course of reacquisition adaptation (see Tables 6 and 7). Although the results showed significant decreases for both deprivation (RA $\beta = -.375$, $p < .001$, 95% CI [–.434, –.315]) and interest (RA $\beta = -.369$, $p < .001$, 95% CI [–.425, –.314]), there was an overlap in the confidence intervals, and the difference test showed no significant difference between these effects (interest $B = -.212$, $SE = .016$; deprivation $B = -.217$, $SE = .018$; $Z = .21$, $p = .836$). These results show decreases in scores for interest and deprivation curiosity are not different in reacquisition adaptation.

Within-Person Relationships with Time-varying Variables

Information-knowledge Gaps as an Antecedent

Hypothesis 4 predicted a positive relationship between information-knowledge gaps and general state epistemic curiosity at the within-person level. This hypothesis was supported by the within-person correlation ($r = .17$, $p < .001$) and the discontinuous mixed-effects growth modeling. For example, the effect was positive and significant in Table 5 Model 3 ($\beta = .036$, $p < .001$, 95% CI [.023, .048]). These findings show there is a positive relationship between information-knowledge gaps and general state epistemic curiosity at the within-person level. This means that increases (decreases) in state epistemic curiosity are greater when increases (decreases) in information-knowledge gaps are greater.

Hypothesis 5 predicted a positive relationship between information-knowledge gaps and general state epistemic curiosity at the between-person level. This hypothesis was not supported by the correlations ($r = .06$, $p = .135$) but was supported by the discontinuous mixed-effects growth modeling (see Table 5). The coefficient was positive and significant in Model 3 ($\beta = .065$, $p < .001$, 95% CI [.008, .121]). The discontinuous mixed-effects growth models provide a stronger test of this hypothesis than correlations as they account for covariates and changes over time (Bliese and Lang, 2016). Overall, these findings show a positive relationship between information-knowledge gaps and general state epistemic curiosity at the between-person level. This indicates that the perception of information-knowledge gaps is important in predicting who might have greater state epistemic curiosity and engagement with learning new tasks.

Hypothesis 6 predicted that the positive association between deprivation curiosity and information-knowledge gaps would be stronger than the association between interest curiosity and information-knowledge gaps at the within-person level. As shown in Model 3 in Tables 6 and 7, although the coefficients for within-person information-knowledge gaps for both deprivation and interest curiosity were positive, as expected, the effects were nearly identical for deprivation ($\beta = .016$, $p = .055$, 95% CI [.000, .031]) and interest curiosity ($\beta = .017$, $p = .029$, 95% CI [.002, .032]). Thus, these results did not show differences in the within-person relationships between information-knowledge gaps and deprivation and interest curiosity. As mentioned above, results for the additional analyses involving the removal of Session 7 and 14 scores, did not change this conclusion. The within-person main effects for information-knowledge gaps as a predictor of the curiosity dimensions were positive, significant, and nearly identical for interest ($\beta = .023$, $p = .004$, 95% CI [.007, .039]) and deprivation ($\beta = .022$, $p = .012$, 95% CI [.005, .039]).

Exploration as an Outcome

Hypothesis 7 predicted a positive relationship between state epistemic curiosity and exploration at the within-person level. This hypothesis was supported by the correlation ($r = .32$, $p < .001$) and in the results of the discontinuous mixed-effects growth modeling. More specifically, Table 8 shows a significant and positive effect in Model 3 ($\beta = .180$, $p < .001$, 95%

CI [.128, .232]). Overall, these findings show there is a positive relationship between state epistemic curiosity and exploration at the within-person level. This means that increases (decreases) in exploration were higher (lower) when individuals experienced increases (decreases) in general state epistemic curiosity.

Hypothesis 8 predicted a positive relationship between state epistemic curiosity and exploration at the between-person level. This hypothesis was supported by the correlation (r = .34, p < .001) and the discontinuous mixed-effects growth modeling. Model 3 in Table 8 shows a positive and significant effect (β = .044, p < .001, 95% CI [.024, .064]). Overall, these findings reflect how exploration was greater for individuals with greater state epistemic curiosity. General state epistemic curiosity is important in predicting who might explore more when learning new tasks.

Research Question 4 addressed whether the association between interest and exploration is stronger or weaker than the association between deprivation and exploration at the within-person level. When looking at the positive and significant within-person correlations, the associations with exploration were similar for interest (r = .29, p < .001) and deprivation (r = .33, p < .001). Likewise, the results of the discontinuous mixed-effects growth modeling in Model 3 in Table 9 showed no difference in the effects for interest (β = .027, p = .003, 95% CI [.009, .046]) and deprivation (β = .024, p = .011, 95% CI [.005, .043]). These results show the magnitude of the positive within-person effects of interest and deprivation curiosity with exploration were not different.

Although not included in my hypothesis testing or research questions, it is also important to address whether the association between interest and exploration is stronger or weaker than the association between deprivation and exploration at the between-person level. The discontinuous mixed-effects in Table 9 showed that the confidence intervals for interest (β = .048, p = .276, 95% CI [–.038, .134]) and deprivation (β = .188, p < .001, 95% CI [.110, .266]) overlapped. With respect to the correlations, the association between state interest and exploration (r = .32, p < .001) was similar to the association between state deprivation and exploration (r = .36, p < .001). In general, these results do not show a difference in effects for state interest and deprivation curiosity at the between-person level.

Furthermore, it is helpful to examine whether there is a difference in model fit between the model adding general curiosity (see Model 3 in Table 8) and the model including interest and deprivation curiosity (see Model 3 in Table 9). The AIC indicated that the model including interest and deprivation (AIC = –8599.48) was a better fitting model in predicting exploration than the model including only general curiosity (AIC = –8584.41). This shows that the inclusion of the interest and deprivation aspects captured nuances important in the prediction of exploration that general curiosity did not.

Following this, Model 4 in Table 9 tested the interaction between trait epistemic curiosity dimensions and their state counterparts at the between-person level (e.g., trait epistemic curiosity interest with state epistemic curiosity interest at the between-person level). There was a significant interaction for trait interest with state interest at the between-person level (β = –.068, p = .003, 95% CI [–.113, –.024]). This indicated that the relationship between state interest and exploration is weaker among individuals higher in trait interest curiosity. However, the AIC indicated that the model not including these interactions was the better fitting model.

Activating Emotions as Antecedents

Activating emotions were included in the present study as controls and were important in the prediction of state epistemic curiosity. Model 3 in Tables 5-7 show several consistencies.

Positive activating emotions had positive effects at both the between- (general state epistemic curiosity β = .274, $p < .001$, 95% CI [.215, .334]; interest β = .296, $p < .001$, 95% CI [.238, .355]; deprivation β = .176, $p < .001$, 95% CI [.115, .237]) and within-person levels (general state epistemic curiosity β = .235, $p < .001$, 95% CI [.209, .262]; interest β = .234, $p < .001$, 95% CI [.202, .267]; deprivation β = .201, $p < .001$, 95% CI [.165, .236]). Additionally, the effects for positive activating emotions were greater than the effects for information-knowledge gaps. The effects for negative activating emotions were negative at the within-person level (general state epistemic curiosity β = –.035, $p < .001$, 95% CI [–.045, –.024]; interest β = –.055, $p < .001$, 95% CI [–.068, –.043]; deprivation β = –.032, $p < .001$, 95% CI [–.046, –.019]). The results were mixed for negative activating emotions at the between-person level (general state epistemic curiosity β = .065, $p = .024$, 95% CI [.008, .121]; interest β = –.046, $p = .118$, 95% CI [–.104, .012]; deprivation β = .008, $p = .792$, 95% CI [–.052, .069]). Overall, positive activating state emotions were positively related to state curiosity with stronger and more consistent effects than the effects for negative activating state emotions.

Discussion

The primary purpose of my dissertation was to examine the theorized longitudinal decline of state epistemic curiosity, an important and untested claim discussed repeatedly in the literature. The secondary purpose was to examine the relationships between state epistemic curiosity with theoretically relevant time-varying variables important for curiosity and learning. In reference to state epistemic curiosity, information-knowledge gaps were examined as a key antecedent and exploration was examined as a key outcome. Differences in effects for interest and deprivation aspects of state epistemic curiosity were compared. The insights from the present study provide a foundation for building theory and practical applications surrounding state epistemic curiosity.

Implications for Theory

Skill Acquisition

During the early stages of learning, learners become aware of information-knowledge gaps (Loewenstein, 1994; Hardy et al., 2019a) which are accompanied by novelty, complexity, and uncertainty, and a spark to curiosity (Berlyne, 1950, 1954). As learners make errors during initial learning (Kanfer & Ackerman, 1989), they experience surprise, confusion, and violated expectations. With practice, learners begin to resolve information-knowledge gaps, master complexity, and habituate to task demands, and in turn curiosity should wane. The perceived novelty and emotional impacts also begin to wane with repeated exposure to task stimuli (Berlyne, 1950). Indeed, my results provided evidence for the longitudinal decreases in curiosity in skill acquisition, with deprivation declining at a greater rate than interest curiosity.

Transition Adaptation

The paradigm in my study introduced a surprise change in task demands involving increases in task complexity. A surprise change in task demands should expose information-knowledge gaps (Hardy et al., 2019a) by violating expectations and introducing novelty and additional uncertainty, and there should be a new spark to curiosity (Berlyne, 1950, 1954). The present results provided evidence for an increase in general state epistemic curiosity with transition adaptation. However, scores for the interest and deprivation dimensions did not increase as expected. The reason for the discrepancy between the scores on the general measure and the dimensions likely involves nuances surrounding the complexity of the change in task demands and possible construct underrepresentation in the measurement of the interest and deprivation aspects.

The surprise change in task demands I manipulated to increase complexity aligned with explanations for increasing curiosity by violating expectations (Loewenstein, 1994), exposing new information-knowledge gaps (Hardy et al., 2024), and spurring preferences for mastering new challenges and complexity (Dember & Earl, 1957; Lang & Bliese, 2009). However, researchers (Hebb, 1955; Loewenstein, 1994; Dember & Earl, 1957) have also described an inverted U-shaped preference for arousal, similar to notions of flow (Nakamura & Csikszentmihalyi, 2002). Learners are bored in the absence of complexity and are overstimulated (i.e., anxious) by too much complexity. Assuming the change in task demands was overwhelming, the anxiety associated with the complexity could have also been taxing to the learners' cognitive resources (Hughes et al., 2013; Westlin et al., 2019). Also, the surprise aspect of the changes could have exacerbated perceived uncertainty. Sources of uncertainty include inconsistency, variety, unpredictability, incomprehensibility, tentativeness, unfamiliarity, disorder, incompleteness, and impermanence (Hillen et al., 2017). It is possible any spark in curiosity from the change could have been offset by an overwhelming amount of complexity and corresponding uncertainty about one's capability to meet new task demands.

Moreover, the single-item measures for interest and deprivation curiosity likely underrepresented elements of their dimensions that would capture a spark in curiosity despite the overwhelming nature of the increased complexity. The item representing interest—"It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me"—tapped into positive emotions with the word "enjoyable." It is possible for individuals to find a surprising and overwhelming increase in task complexity interesting but not enjoyable. Likewise, the item representing deprivation—"I will try to figure it out if something frustrates me about Unreal Tournament"— captures motivation to continue striving (i.e., persistence) in the face of frustration. However, it is possible for individuals to feel deprived of understanding and neither feel frustrated nor motivated to continue striving in the face of a surprising and overwhelming increase in task complexity. It is likely that there are specific elements to interest and deprivation curiosity not represented in the scales used that would show an increase with the task-manipulation I used.

Reacquisition Adaptation

Similar to the circumstances under skill acquisition, after repeated exposure, there will be a resolution of information-knowledge gaps as novelty decreases, complexity is mastered, and familiarity increases. There are fewer instances of confusion and conflict, and learners again become habituated to task demands. Curiosity should again wane. My results provided evidence for the decline of curiosity over the course of reacquisition adaptation for general state epistemic curiosity as well as for the interest and deprivation dimensions. Differences between the dimensions were not observed. In general, the size of the effects were similar for skill acquisition and for reacquisition adaptation for general, interest, and deprivation curiosity.

Altogether, my findings supported longstanding but untested theory about fading curiosity. Fading curiosity occurred both during skill acquisition and reacquisition adaptation, meaning that it occurred before the change in task demands and afterwards. The findings that there was a decline for general, interest, and deprivation curiosity means that it may not matter which type of curiosity is measured to observe this phenomenon. A major contribution of my dissertation is that this is the first longitudinal empirical study to show changes in scores for state curiosity, with fading curiosity as the clear takeaway.

Information-knowledge Gaps as an Antecedent

Information-knowledge gaps have been associated with curiosity since Loewenstein's (1994) review of the literature, and they have been the primary theoretical explanation for declines in state epistemic curiosity. The present study is the first to examine assertions about the role of information-knowledge gaps as a key antecedent of curiosity in relation to fading curiosity and learning. The results showed information-knowledge gaps are in fact an important predictor of state general curiosity and both interest and deprivation aspects. Information-knowledge gaps were positively associated with curiosity and incrementally predicted curiosity above and beyond a variety of control variables such as sex, general mental ability, past experience, trait epistemic curiosity, and emotions.

It was anticipated that deprivation would be more related to information-knowledge gaps than interest because of deprivation's theoretical origins in its association with information-knowledge gaps (Litman, 2008). However, the results did not show a difference between interest and deprivation curiosity in their positive relationships with information-knowledge gaps. The results showing positive relationships of similar magnitude between information-knowledge gaps and interest and deprivation curiosity aligns with Hardy et al.'s (2019a) propositions regarding how information-knowledge gaps reflect a desire for novelty and more complexity as well as an awareness of gaps in knowledge and skill. Information-knowledge gaps are a motivational discrepancy between perceptions of yet to be learned task information and perceptions of well understood task information (Hardy et al., 2024). By showing similar positive associations between information-knowledge gaps and interest and deprivation curiosity, my results suggest perceptions of yet to be learned information (i.e., aspects of the task environment not understood, much less mastered) reflects the anticipated pleasure of new discoveries (i.e., interest) and a desire to reduce the unpleasantness of not knowing (i.e., deprivation). In doing so, a key contribution of my dissertation is showing supportive evidence for Hardy et al.'s (2024, p. 80) assumption that "larger information-knowledge gaps elicit feelings of interest and knowledge deprivation."

Exploration as an Outcome

Exploration has been closely associated with curiosity since Berlyne's (1950) work suggesting curiosity as an important predictor of exploration. My dissertation is the first to examine curiosity as a predictor of exploration using a longitudinal design in relation to fading curiosity. The results showed that curiosity is in fact an important predictor of exploration both at the between- and within-person levels with incremental effects above and beyond each other and the control variables. Thus, curiosity appears to capture unique variance in exploration and potentially other learning processes that are not captured by activating emotions. Additionally, the interest and deprivation aspects together better fit the data than general curiosity in predicting exploration. This suggests that the scores for the interest and deprivation aspects captured different nuances not fully captured in the general curiosity scores in predicting exploration. It also shows the importance for the measurement of both interest and deprivation aspects in research addressing the associations of curiosity with other variables espoused as important to self-regulation, learning, and performance (cf. Huck et al., 2020).

My findings showing that both interest and deprivation state epistemic curiosity were important for predicting exploration also address arguments made by White (1959) in terms of how exploration can stem from a drive to reduce aversive states versus a drive to approach incentives. Consistent with discussion above regarding how perceptions of yet to be learned information are a key component to information-knowledge gaps, deprivation curiosity reflects a drive-reduction state, whereas interest curiosity reflects a drive-induction state. My results showed that both interest and deprivation curiosity yielded positive within-person effects in predicting exploration, and their effects were similar in magnitude. Thus, an important contribution of my dissertation is showing how both drive-reduction and drive-induction aspects of curiosity are important predictors of exploration, and neither state plays a stronger role over the other.

Activating Emotions as Antecedents

Although not central to the hypotheses and research questions, emotions were included as control variables in the present study. There are competing perspectives in the literature on how epistemic curiosity relates to emotions. Some scholars suggest that curiosity is an emotion (Spielberger & Reheiser, 2009; Silvia, 2008a), yet common models of emotions do not include curiosity (Russell, 1980; Smith & Ellsworth, 1985). Others suggest that curiosity has an emotional component (Berlyne, 1954; Rice, 2023).

The present results provided evidence that positive activating emotions were important for predicting curiosity with incremental effects above the control variables. These positive effects were larger than the effects for information-knowledge gaps, showing the importance of positive activating emotions as an antecedent for curiosity. The effects for negative activating emotions on curiosity were smaller compared to those for positive activating emotions at the within-person level. At the between-person level, the effects for negative activating emotions were inconsistent with significant effects for general curiosity but not for interest and deprivation aspects. The negative effects for negative activating emotions predicting curiosity are surprising given that past research on trait curiosity suggests that deprivation should be positively associated with emotions such as anger and anxiety (Litman & Jimerson, 2004). However, my dissertation is the first to look at the association between state curiosity and activating emotions.

These findings have at least two implications. First, positive activating emotions play a much larger role than previously proposed in predicting curiosity. Initial theories by Berlyne and William James described curiosity primarily as an emotion (Loewenstein, 1994). In contrast, Loewenstein (1994) described curiosity as more of a cognitive drive-reduction process with information-knowledge gaps than as an emotion. My results showed that emotional and cognitive antecedents accounted for variance in state epistemic curiosity.

Second, curiosity is more related to positive activating emotions (i.e., enthusiastic, happy, and excited) than negative activating emotions (i.e., angry, anxious, frustrated, irritated, tense, and uneasy). With respect to the mechanisms involved, my results bring clarity to prior theories and suggest that the approach of pleasure (i.e., drive induction) is just as important if not more important to state curiosity than the reduction of unpleasant states (i.e., drive reduction). This follows arguments by Silvia (2008b) suggesting that curiosity is different from but strongly and positively associated with happiness and Junça-Silva and Silva's (2021) findings regarding trait curiosity's associations with positive affect.

Limitations and Future Directions

There are some limitations that should be considered when interpreting these results. First, the generalizability of the study is a concern. Only undergraduate students participated in the present study, and the criterion task was a fast-paced, first-person shooter computer game. The bonus opportunities for high performance may have also impacted participants' decisions to favor improving existing strategies versus exploring new possibilities (Hardy et al., 2019b). Additionally, the 4-hour protocol limits the generalizability to larger intervals of time (e.g., days, weeks, months, and years) and longer-duration learning contexts. This is the first study to examine fading curiosity, and future research should extend the findings to a variety of academic, avocational, and vocational contexts, especially because the magnitude of information-knowledge gaps likely differ across knowledge and task domains (Loewenstein, 1994).

Second, the construct representation of the interest and deprivation dimensions is a concern. Reducing the number of items measuring these dimensions to single items undoubtedly limited construct representation. The single-item measures were likely deficient. Including more items would have ensured better construct representation as well as reliability. Thus, my results likely underestimated the relationships shared between interest and deprivation scores with information-knowledge gaps and exploration. Future research with fuller interest and deprivation scales is needed to provide better estimates of relationships with other variables of interest as well as to better test differential effects.

Third, the task-change manipulation involved several features that make longitudinal claims about curiosity during transition adaptation unclear. Testing a larger variety of distinct manipulations would provide clarity on how curiosity changes when there are changes in task demands. An example of this would be a task change that does not increase complexity. Future research might also address how the longitudinal trajectory of curiosity changes depending on how overwhelming new task demands are across distinct aspects of task complexity. For example, comparing effects in a multifactorial design involving Wood's (1986) three aspects of task complexity—componential, coordinate, and dynamic—would be worthwhile. Componential complexity refers to the sheer number of distinct parts of a task. Coordinative complexity refers to the interdependence among the parts of a task and the extent to which their execution must be integrated. Dynamic complexity refers to the degree of uncertainty in task demands in terms of the inconsistency versus stability in information-processing demands. Despite the present concerns about the longitudinal claims about curiosity during transition adaptation, it was clear that information-knowledge gaps increased (see Panel C in Figure 1). Important theoretical advancements could be made by examining differences between interest and deprivation curiosity as learners experience new information-knowledge gaps during transition adaptation across different, theoretically distinct aspects of task change. Curiosity likely acts as a motivational resource to learners as they ask questions about the uncertainty in task environments.

Fourth, my dissertation covered state curiosity's association with just a small range of the broader network of constructs important for learning and achievement, and there is more to examine about curiosity's associations with information-knowledge gaps and exploration. Hardy et al.'s (2019a) DEEL model offers several variables that would be important to address including how both competence beliefs and novelty motives comprise information-knowledge gaps. As described previously, uncertainty likely plays a role in the longitudinal decline of curiosity (Loewenstein, 1994). Empirical evidence for the between- and within-person association between curiosity and uncertainty perceptions would certainly be useful for advancing further theoretical discussions on the impacts of uncertainty on curiosity. The between- and within-person association would also be useful for disentangling the effects of complexity on curiosity. Adapted state uncertainty measures would be valuable in these efforts.

Hardy et al. (2019b) provided evidence that self-regulated learning processes shape one another, which could be a useful approach for integrating curiosity, information-knowledge gaps, and exploration with reciprocal effects. Exploration was treated as an outcome variable in my dissertation, and the positive association with curiosity was clear. It might also be important to examine exploration as an antecedent as well. This is similar to William James' notions that just as motivation precedes behavior, behavior might also precede motivation (James, 1890). In describing the decline of task exploration in learning contexts, after learners explore and experience negative emotions (i.e., disappointment, anxiety, or frustration), they would likely be less curious and willing to allocate their limited time, attention, and effort towards exploration. This explanation is partially supported by the results of my dissertation with negative activating emotions negatively predicting curiosity and follows the resource-preservation function of the DEEL model as described by Hardy et al. (2019a). Rather than sparking more learning-oriented effort via a deprivation, drive-reduction mechanism, my results suggest that negative emotions likely motivate learners to reallocate attention and effort toward other concerns. This explanation would provide another mechanism for the decrease of exploration via state curiosity beyond information-knowledge gaps.

Conclusion

My dissertation is the first to provide longitudinal empirical evidence for "fading curiosity." This research extends all too common trait approaches to studying curiosity by examining dynamic within-person changes in state epistemic curiosity over the course of learning. My dissertation tested and largely supported long-held but untested assertions about fading curiosity and state epistemic curiosity's association with information-knowledge gaps, emotions, and exploration. Information-knowledge gaps and positive activating emotions more so than negative activating emotions were important predictors of general curiosity as well as both interest and deprivation curiosity. General curiosity as well as both interest and deprivation curiosity were important predictors of task exploration above and beyond emotions. Altogether, my findings advance theory by showing how curiosity's role in learning reflects both drive-induction and drive-reduction processes—the anticipated pleasure found in new discoveries and the satisfaction found in resolving gaps in understanding. My findings position state epistemic curiosity as a distinct and important part of learning, and they lay a foundation for advancing theory on how to spark and sustain motivation in learning and achievement contexts. It is my hope that this study provides a path for practitioners to develop novel interventions to support self-regulation and learning across a wide variety of educational, instructional, training, and development contexts.

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Table 1

Hypotheses and Research Questions

Focus	Hypothesis / Research Question	Results
Curiosity changes during skill acquisition	**Hypothesis 1**: State epistemic curiosity will decrease over the course of skill acquisition (across skill acquisition sessions).	Supported
	Research Question 1: Will interest or deprivation scores exhibit a greater decrease over the course of skill acquisition (across skill acquisition sessions)?	Deprivation showed a greater decrease than interest
Curiosity changes during transition adaptation	**Hypothesis 2**: State epistemic curiosity will increase during transition adaptation (in the first adaptation session after a change in task demands).	Supported for general curiosity Not supported for interest and deprivation
	Research Question 2: Will interest or deprivation scores exhibit a greater increase during transition adaptation (in the first adaptation session after a change in task demands)?	No difference was observed
Curiosity changes during reacquisition adaptation	**Hypothesis 3**: State epistemic curiosity will decrease over the course of reacquisition adaptation (across adaptation sessions).	Supported
	Research Question 3: Will interest or deprivation scores exhibit a greater decrease in scores over the course of reacquisition adaptation (across adaptation sessions)?	No difference was observed
Information-knowledge gaps as an antecedent	**Hypothesis 4**: At the within-person level, there will be a positive relationship between information-knowledge gaps and state epistemic curiosity.	Supported
	Hypothesis 5: At the between-person level, there will be a positive relationship between information-knowledge gaps and state epistemic curiosity.	Supported
	Hypothesis 6: At the within-person level, the positive association between deprivation curiosity and information-knowledge gaps will be stronger than the association between interest curiosity and information-knowledge gaps.	Not supported
Exploration as an outcome	**Hypothesis 7**: At the within-person level, there will be a positive relationship between state epistemic curiosity and exploration.	Supported
	Hypothesis 8: At the between-person level, there will be a positive relationship between state epistemic curiosity and exploration.	Supported
	Research Question 4: Will the association between interest and exploration be stronger or weaker than the association between deprivation and exploration at the within-person level?	No difference was observed

Table 2

Summary of Item Psychometric Properties for Litman (2008) Adapted State Epistemic Curiosity Items Used in Rice (2023)

Dimension	Item Content	*M*	*SD*	Item−total correlation	CFA factor loadings	*r*	Stepwise regression β
Interest							
	2. When I learn something new about Unreal Tournament, I like to find out more about it.	3.43	1.02	.66	.74	.34***	*nr*
	4. It is enjoyable to learn about aspects of Unreal Tournament that are unfamiliar to me.†	3.42	1.08	.76	.89	.44***	.34
	5. I would enjoy discussing Unreal Tournament with others.	3.08	1.18	.62	.79	.37***	.18
	8. I enjoy trying new ideas for playing Unreal Tournament.	3.49	1.04	.74	.84	.36***	*nr*
	9. It is fascinating when I learn something new about Unreal Tournament.	3.12	1.08	.69	.81	.32***	*nr*
Deprivation							
	1. With Unreal Tournament, I feel restless without answers to the problems I have.	2.83	1.09	.34	.31	–.01	*nr*
	3. I can’t stop thinking about the challenges to playing Unreal Tournament.	2.74	1.08	.54	.56	.10	*nr*
	6. I work like a beast at aspects of Unreal Tournament that I feel must be solved.	2.65	1.04	.52	.77	.26***	.15
	7. I will try to figure it out if something frustrates me about Unreal Tournament.†	3.56	1.00	.49	.70	.30***	.22
	10. I dwell about being able to play Unreal Tournament better.	2.79	1.13	.47	.63	.14*	*nr*

Note. $N = 248$. CFA = confirmatory factor analysis. βs and rs are in the prediction of performance scores averaged across adaptive performance sessions. *nr* = not retained in the model. † = item used in the present study. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, two-tailed.

Table 3

Descriptive Statistics and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
Between–person level															
1. Sex	0.48	0.50	-												
2. General mental ability	25.51	4.36	–.19***	-											
3. Videogame experience	0.00	0.85	–.52***	.08*	(.87)										
4. Trait interest	3.93	0.56	–.13***	.12**	.16***	(.79)									
5. Trait deprivation	3.18	0.72	–.09*	.06	.07	.45***	(.76)								
6. Positive activating emotions	3.05	1.55	–.30***	–.01	.23***	.13***	.06	(.87)							
7. Negative activating emotions	3.39	1.75	.21***	–.07	–.14***	–.07	.07	–.13*	(.90)						
8. Information-knowledge gaps	34.38	22.75	.25***	–.08*	–.21***	–.08	–.03	–.02	.04	(.92)					
9. Exploration	0.39	0.13	.16***	–.08*	–.18***	.04	.03	.21***	.05	.25***	-				
10. General state epistemic curiosity	3.35	1.90	–.12**	.00	.17***	.16***	.16***	.53***	–.13**	.06	.34***	-			
11. State interest	2.84	1.01	–.19***	.06	.19***	.22***	.17***	.56***	–.30***	–.02	.32***	.80***	-		
12. State deprivation	3.12	0.94	–.14***	.06	.18***	.26***	.23***	.43***	–.20***	.01	.36***	.70***	.83***	-	
13. Performance	17.72	11.21	–.65***	.24***	.61***	.18***	.11**	.28***	–.28***	–.29***	–.21***	.23***	.32***	.29***	(.78)

	ICC	*M*	*SD*	1	2	3	4	5	6	7	8
Within–person level											
1. Positive activating emotions	.69	3.05	1.90								
2. Negative activating emotions	.79	3.39	2.00	–.09***							
3. Information-knowledge gaps	.73	34.38	29.16	.08***	.09***						
4. Exploration	.40	0.39	0.19	.21***	.05***	.27***					
5. General state epistemic curiosity	.67	3.35	2.29	.51***	–.07***	.17***	.32***				
6. State interest	.66	2.84	1.22	.51***	–.22***	.07***	.29***	.70***			
7. State deprivation	.56	3.12	1.22	.40***	–.12***	.13***	.33***	.61***	.73***		
8. Performance	.68	17.72	13.33	.22***	–.24***	–.25***	–.14***	.16***	.24***	.20***	

Note. $N = 618$. Diagonal values are internal consistencies. Sex: 0 = male, 1 = female. $p < 0.05$, $^{**}p < 0.01$, $^{***}p < .001$, two-tailed.

Table 4

Coding Scheme of Change Variables in Discontinuous Growth Models

Variable	Pre-change period							Post-change period						
Bliese and Lang's (2016) Coding Scheme														
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	6	6	6	6	6	6	6
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
Predictor Variables														
Same-session[a]	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Cross-lagged[b]	0	1	2	3	4	5	6	7	8	9	10	11	12	13

Note. [a]Analyses involving curiosity as the outcome variable involved information-knowledge gaps and emotions as same-session predictors (Hypotheses 4-6, see Tables 5-7). [b]Analyses involving exploration as the outcome variable involved curiosity, information-knowledge gaps, and activating emotions as cross-lagged predictors (Hypotheses 7 and 8, Research Question 4, see Tables 8-9).

Table 5

Discontinuous Mixed-effects Growth Models of General State Epistemic Curiosity

	Model 1		Model 2		Model 3	
Variable	β	CI (95%)	β	CI (95%)	β	CI (95%)
Intercept, γ00	.000	(–.068, .069)	.000	(–.057, .057)	.000	(–.057, .057)
Skill acquisition (SA), γ10	–.331***	(–.408, –.253)	–.309***	(–.385, –.232)	–.275***	(–.352, –.198)
Transition adaptation (TA), γ20	.054***	(.033, .075)	.047***	(.027, .067)	.028**	(.008, .049)
Reacquisition adaptation (RA), γ30	–.389***	(–.433, –.345)	–.339***	(–.382, –.295)	–.295***	(–.341, –.249)
Quadratic skill acquisition (SA^2), γ40	.207***	(.125, .288)	.199***	(.119, .279)	.176***	(.096, .257)
Quadratic reacquisition adaptation (RA^2), γ50	.205***	(.169, .240)	.162***	(.127, .197)	.138***	(.102, .174)
Sex, γ01			.069*	(.002, .135)	.057	(–.010, .125)
GMA, γ02			–.016	(–.072, .040)	–.011	(–.067, .045)
Videogame experience, γ03			.050	(–.014, .114)	.058	(–.006, .123)
Trait interest, γ04			.005	(–.057, .067)	.010	(–.052, .072)
Trait deprivation, γ05			.100***	(.039, .161)	.098**	(.037, .159)
Positive activating emotions Between-person (BP), γ06			.276***	(.216, .335)	.274***	(.215, .334)
Positive activating emotions Within-person (WP), γ60			.236***	(.210, .263)	.235***	(.209, .262)
Negative activating emotions BP, γ07			.091**	(.032, .149)	.091**	(.032, .150)
Negative activating emotions WP, γ70			–.033***	(–.043, –.023)	–.035***	(–.045, –.024)
Information-knowledge gaps BP, γ08					.065*	(.008, .121)
Information-knowledge gaps WP, γ80					.036***	(.023, .048)
AIC	21103.79		20600.00		20587.76	

Note. $N = 618$. Bolded font emphasizes the best-fitting model across all models tested according to the AIC.
Sex: 0 = male, 1 = female. *$p < 0.05$, **$p < 0.01$, ***$p < .001$, two-tailed.

Table 6

Discontinuous Mixed-effects Growth Models of State Interest Curiosity Models

	Model 1		Model 2		Model 3	
Variable	β	CI (95%)	β	CI (95%)	β	CI (95%)
Intercept, γ00	.001	(–.067, .069)	.001	(–.052, .054)	.001	(–.052, .054)
Skill acquisition (SA), γ10	–.408***	(–.509, –.306)	–.390***	(–.490, –.290)	–.374***	(–.475, –.273)
Transition adaptation (TA), γ20	–.018	(–.044, .009)	–.024	(–.049, .001)	–.033*	(–.059, –.006)
Reacquisition adaptation (RA), γ30	–.369***	(–.425, –.314)	–.320***	(–.375, –.266)	–.300***	(–.357, –.242)
Quadratic skill acquisition (SA^2), γ40	.363***	(.256, .471)	.356***	(.251, .462)	.346***	(.240, .452)
Quadratic reacquisition adaptation (RA^2), γ50	.305***	(.258, .351)	.260***	(.214, .306)	.249***	(.202, .296)
Sex, γ01			.060	(–.003, .124)	.058	(–.006, .123)
GMA, γ02			.030	(–.023, .083)	.031	(–.022, .084)
Videogame experience, γ03			.043	(–.019, .104)	.044	(–.018, .105)
Trait interest, γ04			.072*	(.013, .131)	.073*	(.014, .132)
Trait deprivation, γ05			.094**	(.036, .153)	.094**	(.036, .152)
Positive activating emotions Between-person (BP), γ06			.296***	(.238, .354)	.296***	(.238, .355)
Positive activating emotions Within-person (WP), γ60			.235***	(.202, .268)	.234***	(.202, .267)
Negative activating emotions BP, γ07			–.046	(–.104, .012)	–.046	(–.104, .012)
Negative activating emotions WP, γ70			–.054***	(–.067, –.042)	–.055***	(–.068, –.043)
Information-knowledge gaps BP, γ08					.011	(–.043, .065)
Information-knowledge gaps WP, γ80					.017*	(.002, .032)
AIC	15114.10		14596.50		14619.60	

Note. $N = 618$. Sex: 0 = male, 1 = female. *$p < 0.05$, **$p < 0.01$, ***$p < .001$, two-tailed.

Table 7

Discontinuous Mixed-effects Growth Models of State Deprivation Curiosity

	Model 1		Model 2		Model 3	
Variable	β	CI (95%)	β	CI (95%)	β	CI (95%)
Intercept, γ00	.001	(–.064, .066)	.001	(–.055, .056)	.001	(–.055, .056)
Skill acquisition (SA), γ10	–.603***	(–.712, –.495)	–.585***	(–.694, –.477)	–.571***	(–.680, –.461)
Transition adaptation (TA), γ20	–.036**	(–.062, –.010)	–.042**	(–.068, –.016)	–.050***	(–.077, –.023)
Reacquisition adaptation (RA), γ30	–.375***	(–.434, –.315)	–.332***	(–.391, –.272)	–.313***	(–.357, –.250)
Quadratic skill acquisition (SA^2), γ40	.537***	(.422, .651)	.530***	(.416, .644)	.520***	(.406, .635)
Quadratic reacquisition adaptation (RA^2), γ50	.275***	(.225, .325)	.239***	(.189, .289)	.228***	(.177, .280)
Sex, γ01			.065	(–.001, .132)	.059	(–.008, .127)
GMA, γ02			.036	(–.019, .092)	.038	(–.018, .093)
Videogame experience, γ03			.056	(–.008, .119)	.059	(–.005, .123)
Trait interest, γ04			.105***	(.043, .166)	.106***	(.045, .168)
Trait deprivation, γ05			.119***	(.058, .179)	.118***	(.058, .179)
Positive activating emotions Between-person (BP), γ06			.178***	(.117, .238)	.176***	(.115, .237)
Positive activating emotions Within-person (WP), γ60			.201***	(.166, .236)	.201***	(.165, .236)
Negative activating emotions BP, γ07			.008	(–.053, .068)	.008	(–.052, .069)
Negative activating emotions WP, γ70			–.032***	(–.045, –.018)	–.032***	(–.046, –.019)
Information-knowledge gaps BP, γ08					.030	(–.026, .086)
Information-knowledge gaps WP, γ80					.016‡	(.000, .031)
AIC	16016.15		15751.80		15774.75	

Note. $N = 618$. Sex: 0 = male, 1 = female. ‡$p = .055$, *$p < 0.05$, **$p < 0.01$, ***$p < .001$, two-tailed.

Table 8

Discontinuous Mixed-effects Growth Models of Exploration with General State Epistemic Curiosity as a Predictor

	Model 1		Model 2		Model 3	
Variable	β	CI (95%)	β	CI (95%)	β	CI (95%)
Intercept, γ00	.001	(–.056, .057)	.001	(–.053, .054)	.001	(–.051, .052)
Skill acquisition (SA), γ10	–.233***	(–.368, –.099)	–.227**	(–.362, –.092)	–.209**	(–.334, –.074)
Transition adaptation (TA), γ20	.140***	(.106, .173)	.105***	(.107, .174)	.139***	(.106, .172)
Reacquisition adaptation (RA), γ30	–.500***	(–.574, –.426)	–.499***	(–.573, –.424)	–.490***	(–.564, –.416)
Quadratic skill acquisition (SA^2), γ40	.108	(–.033, .250)	.105	(–.037, .247)	.098	(–.044, .240)
Quadratic reacquisition adaptation (RA^2), γ50	.256***	(.194, .317)	.256***	(.175, .298)	.260***	(.199, .321)
Sex, γ01			.060*	(.005, .115)	.045	(–.008, .099)
GMA, γ02			.003	(–.042, .049)	.002	(–.042, .046)
Videogame experience, γ03			–.072**	(–.125, –.020)	–.089***	(–.140, –.038)
Trait interest, γ04			.033	(–.018, .084)	.026	(–.023, .075)
Trait deprivation, γ05			.019	(–.031, .069)	–.004	(–.053, .045)
Positive activating emotions Between-person (BP), γ06			.129***	(.075, .183)	.052	(–.007, .112)
Positive activating emotions Within-person (WP), γ60			.031	(–.014, .076)	.004	(–.043, .050)
Negative activating emotions BP, γ07			.038	(–.017, .094)	.033	(–.022, .087)
Negative activating emotions WP, γ70			.000	(–.017, .017)	.002	(–.015, .018)
General state epistemic curiosity BP, γ08					.180***	(.128, .232)
General state epistemic curiosity WP, γ80					.044***	(.024, .064)
AIC	–8599.48		–8546.15		–8584.41	

Note. $N = 618$. Sex: 0 = male, 1 = female. *$p < 0.05$, **$p < 0.01$, ***$p < .001$, two-tailed.

Table 9

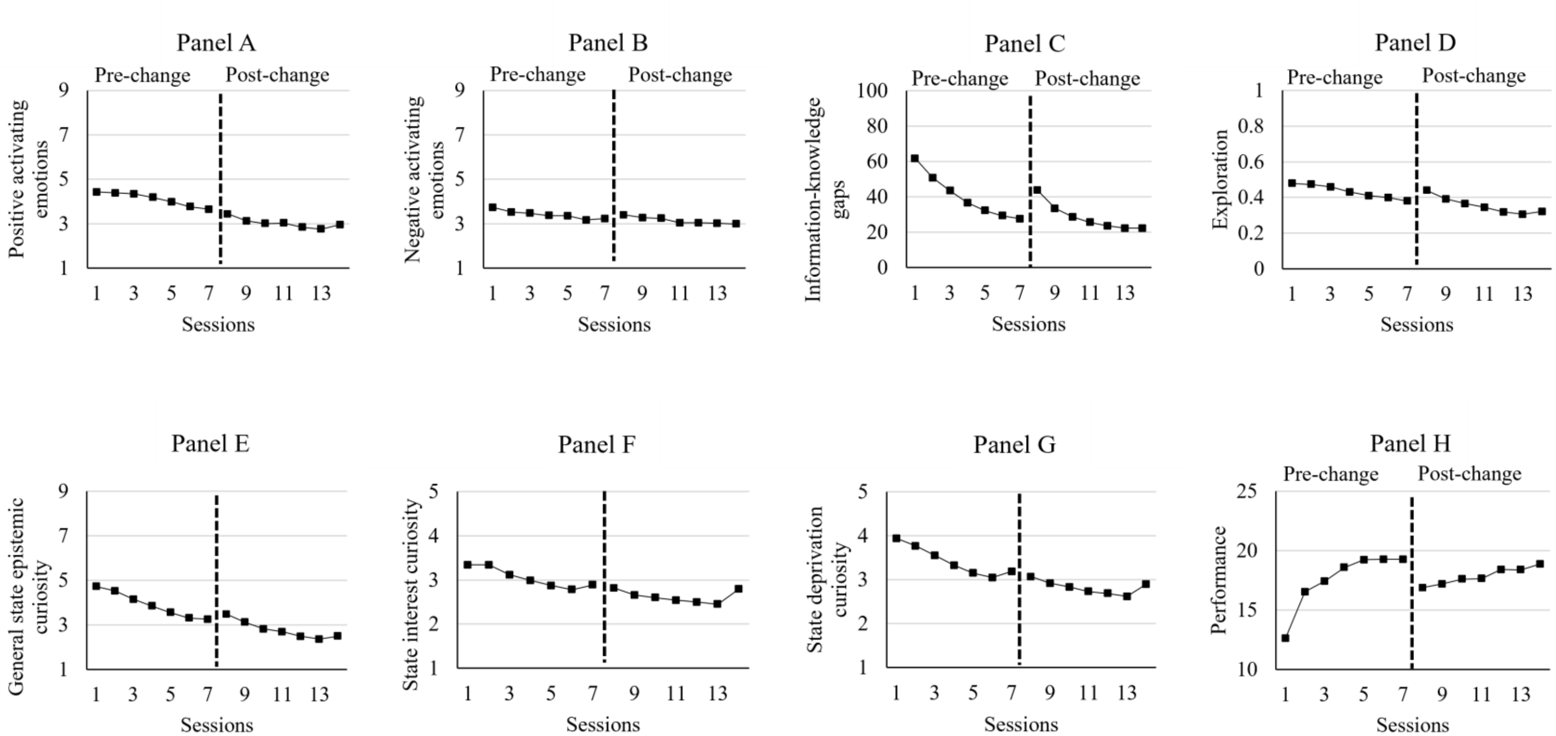
Discontinuous Mixed-effects Growth Models of Exploration with State Interest and Deprivation as Predictors

	Model 3		Model 4	
Variable	β	CI (95%)	β	CI (95%)
Intercept, γ00	.000	(–.050, .051)	.013	(–.038, .065)
Skill acquisition (SA), γ10	–.199**	(–.334, –.064)	–.199**	(–.334, –.064)
Transition adaptation (TA), γ20	.135***	(.102, .169)	.135***	(.102, .169)
Reacquisition adaptation (RA), γ30	–.478***	(–.552, –.403)	–.478***	(–.552, –.403)
Quadratic skill acquisition (SA^2), γ40	.090	(–.052, .232)	.090	(–.052, .232)
Quadratic reacquisition adaptation (RA^2), γ50	.248***	(.187, .310)	.249***	(.187, .310)
Sex, γ01	.047	(–.005, .009)	.045	(–.007, .097)
GMA, γ02	–.009	(–.052, .035)	–.010	(–.053, .033)
Videogame experience, γ03	–.091***	(–.141, –.041)	–.095***	(–.145, –.044)
Trait interest, γ04	.007	(–.041, .056)	–.001	(–.050, .047)
Trait deprivation, γ05	–.019	(–.068, .029)	–.019	(–.067, .029)
Positive activating emotions Between-person (BP), γ06	.052	(–.008, .112)	.059	(.000, .119)
Positive activating emotions Within-person (WP), γ60	.008	(–.038, .054)	.009	(–.037, .054)
Negative activating emotions BP, γ07	.063*	(.008, .118)	.060*	(.005, .115)
Negative activating emotions WP, γ70	.004	(–.013, .021)	.004	(–.013, .021)
State interest curiosity BP, γ08	.048	(–.038, .134)	.047	(–.039, .132)
State interest curiosity WP, γ80	.027**	(.009, .046)	.027**	(.009, .046)
State deprivation curiosity BP, γ09	.186***	(.108, .264)	.183***	(.105, .261)
State deprivation curiosity WP, γ90	.024*	(.005, .043)	.024*	(.005, .042)
Trait interest × state interest curiosity BP, γ041			–.068**	(–.113, –.024)
Trait deprivation × state deprivation curiosity BP, γ051			.010	(–.034, .054)
AIC	–8589.96		–8579.90	

Note. $N = 618$. Models 1 and 2 are shown in Table 8. Sex: 0 = male, 1 = female. *$p < 0.05$, **$p < 0.01$, ***$p < .001$, two-tailed.

Figure 1

Variable Means across Sessions



Note. Trends in study variables over the course of the 14 sessions: 1–7 = pre-change (i.e., acquisition); 8–14 = post-change (i.e., adaptation).