On Affective States in Computational Cognitive Practice through Visual & Musical Modalities

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Academic Abstract

Learners' affective states correlate with learning outcomes. A key aspect of instructional design is the choice of modalities by which learners interact with instructional content. The existing literature focuses on quantifying learning outcomes without quantifying learners' affective states during instructional activities. An investigation of how learners feel during instructional activities will inform the instructional systems design methodology of a method for quantifying the effects of individually available modalities on learners' affect.

The objective of this dissertation is to investigate the relationship between affective states and learning modalities of instructional computing. During an instructional activity, learners' enjoyment, excitement, and motivation are measured before and after a computing activity offered in three distinct modalities. The modalities concentrate on visual and musical computing for the practice of computational thinking. An affective model for the practice of computational thinking through musical expression was developed and validated.

This dissertation begins with a literature review of relevant theories on embodied cognition, learning, and affective states. It continues with designing and fabricating a prototype instructional apparatus and its virtual simulation as a web service, both for the practice of computational thinking through musical expression, and concludes with a study investigating participants' affective states before and after four distinct online computing activities.

This dissertation builds on and contributes to extant literature by validating an affective model for computational thinking practice through self-expression. It also proposes a nomological network for the construct of computational thinking for future exploration of the construct, and develops a method for the assessment of instructional activities based on predefined levels of skill and knowledge.

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General Audience Abstract

This dissertation investigates the role of learners' affect during instructional activities of visual and musical computing. More specifically, learners' enjoyment, excitement, and motivation are measured before and after a computing activity offered in four distinct ways. The computing activities are based on a prototype instructional apparatus, which was designed and fabricated for the practice of computational thinking. A study was performed using a virtual simulation accessible via internet browser. The study suggests that maintaining enjoyment during instructional activities is a more direct path to academic motivation than excitement.

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Contents

List of Figures

List of Tables

1 Introduction

1.1 Instructional Systems

1.1.1 Instructional Computing

Instructional computing is not limited to programming; it refers mostly to instructional activities that are achieved through the use of computers. The learning modality of an instructional activity has an impact on the affective states and self-efficacy of learners, both which promote self-regulated learning [1, pp. 207-231]. A significant aspect of this dissertation is the exploration of self-expressive computing in order to increase the affective quality of instructional activities.

This dissertation contextualizes computational thinking [2] as a cognitive practice, explores the affective quality of computing for self-expression [3], and endorses an experiential approach to learning [4, pp. 121-130], which focuses on learners' affect [5]. An affective model of practicing computational thinking through self-expression is proposed and exemplified by an instructional apparatus that enables visual programming for sound production and musical expression [6, 7, 8, 9]. Empirical evidence is presented from a study that utilized a virtual simulation of the physical instructional apparatus accessible via a web browser. The study investigates the role of learners' affect during three distinct modes of computing: visual programming, visual programming for sound production, and visual programming for sound production including a virtual musical instrument.

The construct of computational thinking postulates that problems and their solutions be described with semiotic resources interpretable by computers. A *semiotic resource* is a coherent pattern of sensory-input regarded as a means for making meaning, such as icons, sound, or text. Computational thinking has been defined as "thought processes" [10] that depend on a set of skills [11, 12, 13, 14, 15, 16, 17, 18]. There are direct (physiological) and indirect (behavioral) ways to measure the intensity of thinking. A direct approach is concerned with physiological data such as “some summary statistic of brain activation.” An indirect approach is concerned with a “person’s score on some behavioral measure” [19, p. 7]. A prevalent indirect approach in previous research focuses on measuring the outcome from practicing computational tasks. For example, an increase in skills that can be observed by means of a pretest-posttest [20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37].

Previous researchers largely agree that computational thinking skills consist of, but are not limited to, the skills of “problem-solving” [38, 39, 40], “code literacy” [38, 40, 41], “pattern recognition” [42, 43, 44], and “data analysis” [40, 45, 46].

1.1.2 Self-Regulated Learning

Self-motivation and *self-regulation* are characteristics of effective learners [47, 48]. Self-regulated learning involves having some control over learning activities [49, 50, 51]. To facilitate self-regulated learning, instructional systems may offer alternative learning modalities for learners to choose from [52, pp. 189-205].

The theory of experiential learning focuses on different models of human affect [53, pp.43-44]. Categorizing learning modalities abstracts learning styles that have been conceptualized to range from a “concrete experience” to an “abstract conceptualization,” and from “active experimentation” to “reflective observation” [54, pp.227-245]. Kolb et al. point out four ”specialized” learning styles that were observed empirically: “Diverging” (concrete experience and reflective observation), “Assimilating” (abstract conceptualization and reflective observation) “Converging” (abstract conceptualization and active experimentation), and “Accommodating” (concrete experience and active experimentation) [54, pp.230-241].

Instructional systems capable of offering multiple learning modalities to accommodate different learning styles or a space among them, are multimodal. Choosing a learning modality is essentially a choice among different semiotic modes that learners may use to make sense of instructional activities [55].

1.1.3 Human-Centered Design

The human-centered approach to design is generally conceptualized in three phases: first, an observation of social activities related the situation of focus drives the *conceptualization* of a problem; second, an iterative process for the *imagination* of possible solutions develops, tests, analyzes, and improves designs; third, the most socially appropriate design solution is chosen for *implementation.*

Factual knowledge about a problem does not equal the understanding of it. Therefore, the first phase seeks to make sense of a problem's inner workings by observing it under real-world conditions. After developing an understanding of the problem, designers ideate feasible solutions, which should then be evaluated for practicality and scalability [56, 57].

Designs can be developed in parallel and/or iteratively. Parallel designing creates competition among designs (inter-design), and iterative designing creates competition among design iterations (intra-design). Inter-design competition explores incompatible solutions in parallel and gathers segmented knowledge, which can accelerate the development of design-solutions. The main advantage of parallel design is that creativity is less restricted by previous choices because designs can fork to enable the exploration of incompatible solutions. The main disadvantage of parallel design is that it does not concentrate resources on one design process. Imagining design-solutions involves parallel design, while implementing design-solutions involves progressive refinement through iterative design [58]. Lastly, it is important to efficiently monitor the implementation of a solution in order to prevent errors or identify them early enough and to manage potential risks.

1.1.4 Virtual-Physical Manipulatives

Instructional manipulatives exemplify concepts and enable self-regulated experimentation. Learners can use manipulatives to explore phenomena and learn by reflecting on their observations. In their work, Weick et al. argue that sense-making "involves turning circumstances into a situation that is comprehended explicitly in words and that serves as a springboard into action"[59, p. 409]. Instructional manipulatives can offer different learning modalities to accommodate different learning styles [60, pp. 35-41][61]. Paek demonstrates "how virtual manipulatives, designed to provide multimodal interactions, support richer perceptual experiences that promote conceptual learning" [62, p. nulla]. Multimodal interaction refers to the multiple ways (modes) with which users interface with learning content.

In formal education, instructional manipulatives may be more or less efficient based on each student's learning style. Sarama and Clements caution us that "students may hold, move, and arrange physical objects without thinking about the concepts" [63, p. 74]. However, as Narayanan et al. point out, "the success of any educational tool or technique largely depends on its successful adoption by both the teachers and students who are the primary stakeholders" [64, p. 299]. Students conceptualize affordances for manipulatives based on available semiotic modes [65, pp. 39-41]. Although physical instructional manipulatives may offer different semiotic resources than virtual manipulatives, a virtual simulation of a physical manipulative could allow the physical and the virtual manipulatives to share learning resources.

1.2 Affective States

1.2.1 Hedonic Tone & Pleasure-Arousal Theory

Hedonic Tone is a measure of the ability to feel pleasure, while anhedonia is the inability to feel pleasure. Keller et al. "found that trait anhedonia was negatively correlated with pleasantness ratings of music stimuli" [66, p. 1319]. Experiencing artwork and making art are known activities with a potential for enjoyment (hedonic usability). Making art is a self-expressive activity. This dissertation proposes that instructional activities based on self-expressive outputs, such as musical expression, could be more engaging due to their enjoyment potential.

The theory of pleasure-arousal conceptualizes a two-dimensional affective state [67]. The two dimensions are the intensity of pleasure, and the intensity of arousal. Pleasure indicates enjoyment, while arousal indicates attentiveness to an experience (incoming stimuli). In recent studies, electro-dermal activity shows evidence that individuals can have multiple states of arousal. For example there have been observed differences between their left and right hands [68]. This dissertation focuses on the conscious and subjective perspective of people experiencing an instructional activity. Therefore, the dissertation's study relies on self-reported measures of affective states.

Betella and Verschure present a measure of pleasure and arousal for ”digital self-assessment,” which is useful for instructional systems [69]. The measure consists of two sliders for the self-assessment of pleasure and arousal. In the dissertation's study, the concept of pleasure is narrowed down to the feeling of enjoyment, and the concept of arousal is narrowed down to the feeling of excitement during an instructional activity.

1.2.2 Motivational Salience

Motivational salience is a measure of an individual's feeling of encouragement (positive) or discouragement (negative) to continue an activity. Zimmerman et al. believe that “perceived efficacy to achieve motivates academic attainment both directly and indirectly by influencing personal goal setting” [47, p. 674]. In other words, learners are self-motivated based on their perception of being able to achieve the challenges they face. Informal education may leverage the interests of learners, but formal education is not as flexible. Wlodkowski argues “that with student motivation, when only one thing goes wrong, the entire process may come to a complete stop” [70, p. 12]. Monitoring learners' affect during instructional activities could be used to assess the efficiency of the activities [71].

Formal education operates within a schooling framework that does not make it easy to customize educational paths. In the context of primary and secondary education, Druin discusses the child student “as user,” “as tester,” “as informant,” and “as design partner” [72, pp. 3-13], and quotes a child that expresses the desire to have fun while learning by playing with friendly and interesting tools. To assess academic motivation, Jones developed the "MUSIC Model of Motivation," a measure "that can be used by instructors to design courses that will engage students in learning." This model suggests "a social-cognitive theoretical framework, in which five factors lead to increased student motivation, resulting in increased student learning." The five factors are: "eMpowerment," "Usefulness," "Success," "Interest," and "Caring" [73, p. 273].

1.3 Self-Expression

1.3.1 Communication

Conscious learning includes communication as a way of making meaning. The principle of embodiment unifies affect and cognition. It assumes that conscious perception is regulated by the nerve sensorimotor system [74, 75]. Conscious perception is therefore subject to the state of the sensorimotor system. This means that unconscious learning encapsulates conscious learning. When communicating via languages human sensorimotor processes the signifier (stimulus) unconsciously, and cognition processes the signified (meaning) consciously.

In semiotics theory, visual communication can involve an iconic sign system [76], and also a symbolic sign system through written language. Both symbolic and iconic sign systems are semiotic resources; however icons are referents themselves, while symbols have external referents expected to be present in people's knowledge. For example, with spoken or written language, a person could communicate the same message (words) to two different people who may make sense of two different messages depending on their individual knowledge and their physical state.

Another sign system, the indexical (deictic), is effectively incomplete. Specific context is necessary to specify the signified less abstractly, and thus to make more specific sense of such communication [77]. For example, the *third study* refers to a study that in some specific context is third. *This dissertation* refers to itself, while *a dissertation* refers abstractly to the concept of a dissertation. Different modes of communication could be constructed by blending different sign systems [78].

1.3.2 Musical Expression

While listening to and making music are both a form of self-expression, making music depends on planned behavior (goals) for the creation of a musical structure. Here, it is important to differentiate between musical expression and musical expressiveness. The former pertains to the production of musical signals, while the latter pertains to the capability of differentiating a musical signal.

Personal computers have made it easy for people to record and process sound using off-the-shelf equipment. The paradigm of the music sequencer (software) enables individuals to compose and produce music without physical musical instruments. However, another paradigm, the real-time synthesis engine, enables individuals to redesign the sound production while the sound is being generated.

This dissertation develops an instructional apparatus based on the real-time synthesis engine paradigm to enable users to practice computational thinking through sound production.

1.4 Research Characterization

The learning modalities of instructional systems for the practice of computational thinking are under-investigated [23, 78, 56]. This dissertation designed and performed an exploratory study of learning modalities for the practice of computational thinking.

The dissertation's study combined exploratory, descriptive, and correlation research into an experiment for the exploration of learning modalities among general public users. The study gathered demographic data and descriptive statistics in order to analyze the relations between measures of affective states and computational knowledge within for groups of participants. Because of its exploratory character and limited sample, the study's objective was not to create normative data. Rather, it was to use empirical data to inform instructional systems design theory.

1.5 Methodological Contributions

This dissertation presents a methodological approach in instructional systems design for the practice of computational thinking through computing for self-expression. The proposed methodology blends visual programming with sound production and with physical-virtual manipulatives to develop a semiotic multimode for the practice of computational thinking.

The importance of this research is in its potential to provide new and improved strategies for introducing computational thinking practice in formal education via practical and potentially enjoyable instructional activities. The proposed methodology includes a novel method for the assessment of computational thinking.

More specifically, the methodological contributions of this dissertation are:

1. A novel nomological network for the construct of *Computational Thinking*. The nomological network is premised on the "bounded rationality" principle [79, pp. 697-699];

2. An experimental investigation of the affective quality of visual and musical modalities in the context of computational cognitive practice;

3. A novel method of instructional assessment based on predefined levels of thinking and knowledge. The proposed method is exemplified using Bloom's revised taxonomy [80], and

4. A novel methodology for the development of physical-virtual manipulatives for the practice of computational thinking that focuses on sharing learning resources between a physical manipulative and its virtual simulation.

2 Literature Review

2.1 Embodied Cognition

2.1.1 System-View of Embodiment

Action within an environment leads to a sense-making process that has the potential to develop new, and to reshape prior knowledge [59]. Meier et al. comment that "current embodiment research in social psychology typically aims to identify whether a concept or related metaphor is embodied" [81, p. 5]. Communication among people is based on semiotic resources. When an idea is expressed through semiotic resources, then it is theorized that the physical object(s) mediating these semiotic resources embody that idea.

Johnson and Rohrer describe embodied cognition by summarizing how some "pragmatist philosophers viewed cognition" [82, p. 2]:

> (1) Embodied cognition is the result of the evolutionary processes of variation, change, and selection.
> (2) Embodied cognition is situated within a dynamic ongoing organism-environment relationship.
> (3) Embodied cognition is problem-centered, and it operates relative to the needs, interests, and values of organisms.
> (4) Embodied cognition is not concerned with finding some allegedly perfect solution to a problem, but one that works well enough relative to the current situation.
> (5) Embodied cognition is often social and carried out cooperatively by more than one individual organism.

In the context of the *pragmatism view*, instructional systems should be capable to evaluate how well they work for their users [83]. Theoretically, instructional systems that offer multiple semiotic modes, could create multiple learning pathways for users, even though not all of them may prove helpful. Self-regulated learning depends on having the ability to choose learning paths that make more sense and are more desirable. Design principles for instructional systems depend on the system's conceptual components.

Most of what the human body perceives with its senses does not pass into conscious awareness. Rather, stimuli are aggregated before being processed on the conscious level. Varela et al. make two points about the influence of bodily actions on cognition: "first, that cognition depends upon the kinds of experience that come from having a body with various sensorimotor capacities, and second, that these individual sensorimotor capacities are themselves embedded in a more encompassing biological, psychological, and cultural context" [84, p. 173]. Gibbs identifies three system-views of embodiment:

1. "the neural level,"
2. "the phenomenological conscious experience," and
3. "the cognitive unconscious" [85, pp. 39-40].

Brain imaging techniques create snapshots of brain activation to describe neurological patterns. In the *neural* perspective, cognition is embodied. This means that the accuracy and precision of awareness is influenced by sensorimotor activity. Aleksander et al. discuss the human "mind's eye" as well as the "learning and remembering" to point out that "the sensory strip in the cortex" and "patterns in the brain are related to where bits of our body are and what they are sensing" [86, pp. 162-165]. Debarba et al. point out that "experimental protocols have shown that the sense of embodiment is much more malleable than commonly assumed" [87, p. 2]. A summary of the system-view of neural-level embodiment is offered by Gaiseanu, who links it to consciousness. Which "is mainly manifested by data accumulation, informational operability, emotional reactivity, functional self-control, associativity and creativity, self-confidence, on the basis of the genetic inheritance of species, received from the parents" [88, p. 14]. Literature of neuroscience offer in-depth explanations of the embodiment principle. For example, Johnson and Rohrer argue that "one of the most profound findings in neuroscience is that nervous systems exploit topological and topographic organization" [82, p. 7].

The phenomenological conscious experience discusses the sense-making process, which "includes all our unconscious knowledge and thought processes" [85, p. 40]. Gallagher and Zahavi argue that "the first-person point of view on the world is never a view from nowhere; it is always defined by the situation of the perceiver's body, which concerns not simply location and posture, but action in pragmatic contexts and interaction with other people" [89, ch. 4].

The cognitive unconscious refers to the information processing occurring in the human body without conscious awareness of it. Gibbs sums a system-view of cognitive unconscious embodiment as "all the mental operations that structure and make possible conscious experience, including the understanding and use of language" [85, p. 40]. Kihlstrom points out that "research on perceptual-cognitive and motoric skills indicates that they are automatized through experience, and thus rendered unconscious." "In conversational speech, for example, the listener is aware of the meanings of the words uttered by the speaker but not of the phonological and linguistic principles by which the meaning of the speaker's utterance is decoded" (phonological as in speech sounds) [90, p. 1447]. The cognitive unconscious system-view is concerned with identifying the unconscious processes that enable conscious awareness.

2.1.2 Notions of Embodiment

This section briefly presents "different notions of embodiment" that are discussed by Ziemke in more detail [74, p. 1306]. In the context of instructional systems design, each notion promotes different design principles for instructional systems.

Structural Coupling

The structural coupling refers to the relationship between the environment and any individual agent it encapsulates. In such interactive ecosystem, both can affect each other's state. Structural coupling may occur via physical or virtual means. Virtual reality could enable the communication of an agent with computer generated and remote physical environments. In this dissertation, the coupling between an agent and its surrounding environment is labeled *natural,* while the coupling, via virtual means is labeled *artificial.* Further, predefined agentive or environmental behaviors are labeled *fixed*, while dynamic behaviors are labeled *dynamic.*

Historical Evolution

With time, a structural coupling is undergoing sequential changes. In other words, structural couplings may have a history of changes that characterize the conditions during these changes. More specifically, a progression of changes reveals which endpoint of the coupling initiated an adaptive change in response to the other endpoint's behavior. The embodiment principle postulates that the cognitive development of an agent is difficult to distinguish from (confounded with) the historical evolution of the environment encapsulating that agent.

Social Interaction

A social interaction is based on the notion of recurring environmental conditions. This notion of embodiment views social links to surrounding agents as part of the environment a focal agent is coupled with. The focal agent perceives other agents' behavior as environmental conditions [91, 92]. Thus, each agent although encapsulated by the same environment expresses a distinct interpretation of the same environmental conditions.

Physical Artifact

A physical artifact reacts to its surrounding environment. The key aspect of this notion of embodiment is the encapsulation of a physical structure by its surrounding environment. *Passive* artifacts react to environmental change, while *active* artifacts enact towards predetermined goals with or without environmental change.

Automaton

An automaton presumes self-actuating capability. This concept is similar to an active physical artifact. The difference between the two is that an automaton is capable of adaptive behavior based on some dynamic model of sensorimotor abilities. Conceptually, the automaton is the blend of an active physical artifact and historical evolution. Nevertheless, an automaton does not learn how to interpret the same stimulus in different ways.

Organism

An organism, however, learns how to interpret the same stimulus differently based on experience (historical evolution). Its behavior is driven by sense-making of both internal and external stimuli. This means that an organism is capable of altering its decision making rule-set (logic). Johnson and Rohrer point out the social aspect of the "organism-environment coupling" and argue that for organismic cases "starting with single-cellular organisms and moving up by degrees to more complex animals. In every case we can observe the same adaptive process of interactive co-ordination between a specific organism and recurring characteristics of its environment" [82, p. 6].

2.1.3 Embodiment in Learning Theories

Behaviorism theory conceptualizes learning as a measurable process. When learners successfully achieve predefined objectives, then they exhibit the abilities necessary for achieving these objectives. Therefore, the successful performance of predefined objectives serves as a measure of learning. Behaviorism seems in alignment with the neural-level system-view of embodiment [93].

Cognitivism theory conceptualizes learning as information meta-processing. Learners make sense of perceived information, and then create or reshape knowledge to be memorized. Cognitivism's perspective disagrees with behaviorism's view of thinking as a behavior, because thinking is conceptualized as a driver of behavior. Cognitivism seems in alignment with the phenomenological conscious experience system-view of embodiment [94].

Connectivism theory conceptualizes learning as information gathering from a network of physical and digital sources. It focuses on the means and modes of retrieving information, rather than on cognitive mechanisms. A principle of connectivism is that there are multiple styles of learning. Moreover, informal learning is emphasized as the norm in the digital era of the internet. This perspective seems in alignment with the phenomenological conscious experience system-view of embodiment [95, pp. 53-68].

Constructivism theory conceptualizes learning as the sense-making of personal experience. People construct meaningful ideas based on how what they are experiencing makes sense to them. In such perspective, predefined learning objectives should describe both the context and content of learning. Constructivism seems in alignment with the unconscious cognition system-view of embodiment [96].

Humanism theory conceptualizes learning as a self-defined process according to individual ability and values. Learning should be customized for the ability and objectives of the learner. Such approach suggests that education should facilitate self-regulated learning based on learners' predefined objectives. Humanism seems in alignment with the unconscious cognition system-view of embodiment [97].

In the context of situated learning, the interaction of learners with the learning content is moderated. Hwang and others describe and discuss the "situated reflective learning model" [98, p. 142]. Reflection is a learning principle in the theory of constructivism. The theory of connectivism suggests that a single semiotic resource provides a single communication channel, while more than one semiotic resource could provide multiple communication channels. Instructional systems that offer multiple communication channels may appeal to a broader community of learners.

There are some fundamental questions when designing instructional systems:

a. *Will it be possible to assess users on what are desired semiotic modes before presenting learning content to them?*

b. *Will the system be able to learn from users' reflections?*

Weliweriya and others argue that "to better represent an idea or a concept, students should be able to strategically combine multiple semiotic resources" [99, p. 3]. This dissertation presumes that more users will be able to explore and express ideas when practicing with systems that enable them to choose from a variety of available semiotic resources [100, pp. 233-249].

The technological progress made small-scale robotics cheaper and commercially accessible. Kennedy et al. argues that "the application of social robots to the domain of education is becoming more prevalent" [101, p. 293]. Simple robotics could be used as learning manipulatives in education that offer programmable features based on their degrees of freedom. Fischer et al. researched the interaction between humans and robots and their "investigation has shown that not only the robot's physical embodiment, but also its degrees of freedom influence human-robot interaction" [102, p. 469]. Instructional activities for cognitive practice could exploit robotic systems as instructional platforms.

There are many theories of cognition. Newell suggests what should a unified theory of cognition address [103, p. 15]:

> Problem solving, decision making, routine action
> Memory, learning, skill
> Perception, motor behavior
> Language
> Motivation, emotion
> Imagining, dreaming, daydreaming, ...

Newell also describes a learning theory, "the SOAR Qualitative Theory of Learning" [103, p. 317]:

1. All learning arises from goal-oriented activity
2. Learn at a constant short-term average rate .5 chunk/sec (the impasse rate)
3. Transfer is by identical elements and will usually be highly specific
4. Learn the gist of a sentence, not its surface structure, unless focus on it
5. Rehearsal helps to learn, but only if do something (depth of processing)
6. Functional fixity and Einstellung will occur
7. The encoding specificity principle applies
8. The classical results about chunking (such as for chess) will hold

"Einstellung" refers to a set of problem-solving techniques that are prior knowledge for an individual. The Einstellung effect is the predisposition of each individual to attempt problem-solving based on their prior knowledge in problem-solving. The "chunking" refers to learning in terms of short-term realizations of facts, concepts, procedures, and self-reflections, while "transfer" refers to the application of prior knowledge and skills to new contexts [103, p. 317].

2.2 Sense-Making

2.2.1 Semiotic Resources

Semiotic resources are the building-blocks of semiotic modes. However, not all semiotic resources have the same level of preciseness when it comes to communicating meaning. Different types of semiotic resources use different types of communicational signage. Three basic types of signage are labeled to describe the relation between signifier and signified: *iconic, indexical, and symbolic.* An icon-sign is supposed to resemble the form of the signified. An index-sign should resemble an indication of the signified such as an antecedent or a consequent. Lastly, a symbolic-sign is linked to meaning by social convention. Individuals must learn symbolic relationships in order to interpret symbolic-signs.

2.2.2 Semiotic Modes

A *semiotic mode* is a cultural structure of semiotic resources. Consequently, a *semiotic multimode* is a coherent aggregate of semiotic modes. Nigay and Coutaz define a semiotic mode with a software engineering perspective: "mode refers to a state that determines the way information is interpreted to extract or convey meaning" [9, p. 172]. A multimodal system operates based on one or more multimodes. The approach to multimodal analysis differs depending on the objective of the analysis.

Jewitt discusses "three approaches within multimodality" that "can be roughly categorized" as "a social semiotic approach to multimodal analysis," "a systemic functional grammar (SFG) multimodal approach to discourse analysis," and "multimodal interactional analysis" [104]. This dissertation borrows elements from the first and the last approaches. Social semiotics is useful in analyzing a visual learning modality, while the interaction analysis is useful in analyzing an auditory learning modality.

Multimodality is often used to describe the input modes for human-computer interaction, such as touch, speech, and motion gestures. However, the concept of multimodality is not limited to input-data analysis. In the context of instructional activities, multimodality characterizes the system's semiotic resources that users are exposed to. Users engaging with a multimode do not necessarily focus on each individual mode. Nevertheless, each individual mode provides stimuli for learners to focus their attention to.

2.2.3 Inter-Relations of Semiotic Resources

An *inter-semiotic resource relationship* is one or more relations between two or more semiotic resources. Inter-semiotic relationships among modes emerge from relations between the attributes of semiotic resources. Instructional design could leverage inter-semiotic relationships to combine modes into multi-modes. For example, playing a violin in an apartment can be loud for neighbors. Playing an electric violin can be even louder when using loudspeakers, but it can also be much quieter when using headphones. However, the goal of sound production is the same when playing the electric violin using either loudspeakers or headphones.

Inter-semiotic relationships instigate "syllogisms" across semiotic modes [103, pp. 378-410]. For example, empirical observation of discrepancies between expected and observed system behavior can instigate reflections on false expectations. Heuristic learning takes place when instructional system users troubleshoot unexpected system behavior.

2.2.4 Affordances of Semiotic Modes

Each *affordance* of a semiotic mode is a possible and straightforward way of applying the semiotic mode in a task. Francesconi argues that "some of the pillars of the embodiment paradigm that correspond—in spite of the classical cognitivism—to key concepts in education are the role of subjective experience (first-person perspective), the body (embodied cognition), the environment (embedded cognition), and the situation/ experience (situated cognition)" [105, p. 264]. No matter which affordances were intended by semiotic mode designers, learners may not recognize them.

An assumption of the embodiment principle is that individuals who pay more attention to certain semiotic resources will be biased towards these resources during their sense-making. Similarly, individuals are biased towards the affordances they perceive, thus ignoring affordances they fail to perceive. For example, an individual pays more attention to the lyrics of a song, while another individual is more attentive to instrumental musical elements of the same song. In another example of complementary resources, individuals proficient in the spoken language may pay little attention to captions of audiovisual content.

Deixis is the use of deictic expressions when describing events or ideas. For example, consider the question: *do you like this?* What does the word *this* denote when it is used as a demonstrative pronoun? The meaning depends on what is being demonstrated by the person asking the question. An assumption of deictic cognitive function is that sense-making is coupled to sensorimotor [106, 107, 108]. Human languages use deictic words to reference objects by means of demonstration. Bergen and Plauche label and exemplify a few linguistic constructions and their relational features [109, p. 34]:

i. Infinitival existential	There's the shopping to do.
ii. Ontological existential	There is a Santa Claus.
iii. Presentational existential	There walked into the room a camel.
iv. Evaluative existential	There's brie and then there's brie.
v. Strange existential	There's a man been shot.

2.3 Computational Thinking

2.3.1 Conceptual Definitions

It is important to identify definitions that are helpful in introducing computational thinking both in formal and informal educational settings. Kale et. al define computational thinking with the following steps: "Confrontation," "Decomposition," "Pattern recognition"; "Abstraction"; "Algorithm/Automation," and "Analysis" [110]. Borges et al. describe the "relations between formal thinking and computational thinking" (the formal operational thinking stage of cognitive development ranges from around 11 years to adulthood) and describe the "computational thinking elements related to digital fabrication activities" as: "Algorithm thinking," "Abstraction," "Decomposition," "Generalization," "Evaluation," and "Data manipulation" [111]. Contrary to skills-based definitions of computational thinking, Wing defines computational thinking as "the thought processes involved in formulating a problem and expressing its solution(s) in such a way that a computer —human or machine— can effectively carry out." Wing also points out that "the most important and high-level thought process in computational thinking is the abstraction process" [112, p. 8].

In appendix 6, table 15 presents definitions of, and perspectives on computational thinking from relevant literature. These findings are grouped under different labels to describe a group's common characteristic. Rose et. al. report on common concepts in the definitions of computational thinking found in their literature review [113, p. 299]:

- Abstraction and generalisation (removing the detail from a problem and formulating solutions in generic terms)
- Algorithms and procedures (using sequences of steps and rules to solve a problem)
- Data collection, analysis and representation (using and analysing data to help solve a problem)
- Decomposition (breaking a problem down into parts)
- Parallelism (having more than one thing happening at once)
- Debugging, testing and analysis (identifying, removing and fixing errors)
- Control structures (using conditional statements and loops)

Instruction is sufficient to introduce concepts, but insufficient to develop skill. While concepts need to be understood, skills need to be practiced. Harel and Koichu characterize "learning as a multi-dimensional and multi-phase change occurring when individuals attempt to resolve what they view as a problematic situation" [114, p. 115]. Designing instructional activities should not simply be a matter of delivering information, but also an environment to with which to apply the instructional content. Authors Barr and Stephenson, Roman-Gonzalez et al., Yadav et al., Curzon et al., Harel and Koichu, Gibson, and Bransford et al. have developed computational activities for the practice of computational thinking [46, 115, 116, 117, 114, 118, 119].

In the context of the visual-dataflow programming paradigm, Turchi and Malizia point out that "visual-programming environments [...] are relatively easy to use and allow novices to focus on designing and creating while avoiding the issues of the traditional murky and complicated programming syntax." The authors introduced "TAngible Programmable Augmented Surface (TAPAS), a system that allows users to adapt a public display's features to their own needs, by using the movements of their smartphone to interact with it" [120, pp. 2-3]. Visual-programming is based on the paradigm of digital abstractions [121, 122]. Visual-dataflow programming renders data connections visible by mapping them out on screen.

Practicing computational thinking within a creative context, such as music making, may help learners stay motivated to practice due to the self-expressive creative output. Hidi and Renninger argue "the level of a person's interest has repeatedly been found to be a powerful influence on learning" [123, p. 111].

2.3.2 Quantification

Different ways for the quantification of computational thinking have been suggested and tested, and few of them even implement automated assessment. Moreno-Leòn and Robles developed "a web tool to automatically evaluate scratch projects" [124]. An approach to real-time automated assessment of skills related to computational thinking is discussed by Koh et al. and is based on recognizing design patterns [125, 126, 127].

Another approach by Moreno-Leòn et al. developed software to calculate "Halstead's metrics" for the evaluation of *Scratch* programs [128, p. 1040]. Halstead's metrics were developed to measure software complexity, thus the authors used software complexity as evidence of knowledge on computational practices [129]. Such approach implicates the measurement of computational thinking by combining it with the ability to express it through a specific programming environment. The measurement of computational thinking through specific programming environments is a common practice. Atmatzidou and Demetriadis report that "the different modality (written and oral) of the Computational Thinking skill assessment instrument may have an impact on students' performance" [18, p. 661]. Curzon et al. believe that assessing skills related to computational thinking "can be done using an adapted version of the existing subject framework for the computing subject itself" [117, p. 7]. This means that each instructional activity should also provide its own measure of computational thinking specific to that activity.

Korkmaz et al. developed a measure "that could be used in the identification of the computational thinking levels of students" [130, p. 568]. This measure collects self-reported data, and the authors perceive computational thinking as "a method of problem solving, system designing and also a method of understanding the human behaviors by drawing attention to the basic concepts of the science of computer" [130, p. 558]. A general approach to measuring computational thinking can be achieved using predefined levels of knowledge and thinking.

A problem with measuring self-reported data is that it weakens the measurement's objectivity. Additionally, self-reported data may be misleading due to social and personal factors. Also, creative programming outputs do not tend to be as optimized as software engineering outputs. Wangenheim et al. believe that "in practice it may be difficult to provide personalized, objective and consistent feedback." Wangenheim et al. based their computational thinking measure on "executing the code and comparing the generated output to the control output" [131, p. 125].

Ioannidou et al. report that with a "phenomenalistic analysis for thousands of games and simulations developed by AgentSheets users over the years, we created a list of basic and advanced Computational Thinking Patterns" [132, p. 6]. These patterns enabled a semantic characterization of code submitted to the AgentSheets platform. Chang et al. used language recognition to assess computational thinking based on weights of programming blocks in the *Scratch* visual-programming environment [133]. To promote assessment automation, Fuentes Pérez et al. used "amCharts" to present data by graphics that "can be downloaded, exported, or printed from the platform itself" [134, p. 792].

2.3.3 Educational Applications

Kalelioglou et al. reviewed 125 papers of relevant literature and suggest that "it can be beneficial to teach Computational Thinking by starting discussions on the following: how to teach Computational Thinking skills, how to assess if our students really have Computational Thinking skills, and how to assess if our students can adopt Computational Thinking skills into real-life situations" [135, p. 592]. These suggestions imply that computational thinking depends on levels of knowledge and skill. While knowledge can be communicated, skills must be practiced. Hence, computational thinking must be practiced.

In the context of formal education, Silva et al. argue "teaching computational thinking is directly associated with constructionism and is essential for the complete – and not only superficial – assimilation of knowledge. Computational thinking is related to the ability to abstract knowledge in different dimensions, while constructionism emphasizes the importance of shaping absorbed knowledge" [17, p. 285]. The authors also report that "approaches that aim to introduce computational thinking to high school students using unplugged computation are unknown" [17, p. 288].

What skills should be practiced to develop computational thinking? Lockwood and Mooney review relevant literature and report seven-stages from elementary to advanced skills related to computational thinking [136, p. 26]:

1. "Animations – watching a movie or similar"
2. "Interactive simulations – a simulation which the user can alter certain parameters"
3. "Collective simulations – like above but with a social element"
4. "Construction set simulations – construction kits used to solve domain-specific problems"
5. "Pattern based authoring – begin to design the behaviours of simulations actors"
6. "End user programming – using tools like AgentCubes or Scratch"
7. "Traditional programming – using languages such as Java or C++"

Moreno-León and et al. specify a weight for each skill related to computational thinking. The authors determine that the effects of computational thinking are explained "27%" by "reasoning ability, visual ability, verbal ability, and numerical ability," while "24%." are explained by "non cognitive personality factors." The remaining "49%" remains unexplained, and the authors conclude that "the best scientific knowledge on the topic to this date seems to indicate that the most effective way to foster computational thinking from early ages is by including programming activities in the school curriculum" [137, p. 1685].

How could skills be practiced? Hsu et al. report "16 learning strategies" [138, p. 302]:

> Project-based learning, problem-based learning, teacher-centered lectures, collaborative learning, game-based learning, aesthetic experience, concept-based learning, systematic computational strategies, scaffolding, problem-solving systems, storytelling, embodied learning, universal design for learning, HCI teaching, design-based learning, and critical computational literacy.

How could formal educational activities be assessed? Hsu et al. argue "because different learning strategies and subjects will be applied at different ages, formal and informal courses also need different scoring guidelines. Such assessment may be of help later in designing teaching activities and modifying teaching strategies" [138, p. 308]. Ilic et al. "determined that parametric analysis techniques and content analysis techniques were the most frequently used data analysis methods in the reviewed studies on Computational Thinking" [139, p. 146]. The authors also suggest that Computational Thinking research has focused on education and instructional technology and their "main findings in studies conducted on Computational Thinking" include "findings on the position of Computational Thinking in curricula and education" [139, p. 142]:

> 1. Computational Thinking should be integrated to education
> 2. Curricula should be reorganized based on Computational Thinking skills
> 3. Computational Thinking is useful in courses
> 4. Computational Thinking should be included in teacher training

Formal education lags behind informal education in utilizing instructional activities based on robotic platforms. Ioannou and Makridou discuss "educational robotics" [140, p. 2533]:

> In terms of assessment, efforts have been made to assess Computational Thinking in the context of using visual languages to teach programming and Computational Thinking skills. Among others, Koh et al. (2010) proposed another two approaches: The Program Behavior Similarity (PBS) and the Computational Thinking Pattern Graph (CTPG) in which student-created games and simulations are analyzed towards depicting the Computational Thinking concepts implemented by the students.

Lastly, the blend of visual and text-based programming can be very powerful for learning, because once an abstraction has been designed in a text-based environment, then it can be represented visually by means of inputs, attributes, and outputs. Massive Open Online Courses (MOOCs) have made it easy to seek knowledge online. Free/Open Source Software (FOSS) offers free and easy access to practice through digital media. As Hanna points out, "reading masterful source code teaches the student good programming habits" [37, p. 5]. Also, Lu and Fletcher suggest "the emphasis should be on understanding (and being able to manually perform) computational processes, and not on their manifestations in particular programming languages" [141, p. 261]. Most visual-programming environments do not help users to transition to text-based programming environments. Vanvorce and Jamil discuss the transition from visual to syntax-based programming. In their approach, "code*Mapper,*" "students write codes or import codes in text-based languages, and thus they must be somewhat familiar with the syntax" [142, pp. 2-3].

In Appendix 6, Table 16 reports on the teaching modules used in curricula of computational thinking pertaining to all education levels, and even to professional development. Additionally, Table 17 describes educational tools and their respective components or activities aiming to the development of skills commonly related to computational thinking.

2.3.4 Gamification and Musical Expression

Playing games is an enjoyable activity for many, particularly for children and teens. For this reason, Boulton et al. propose that "game jams can support engagement with informal learning beyond schools across a range of disciplines, resulting in an exciting experience associated with strong, positive emotions which can significantly support learning goals" [143]. In another example of practicing computational thinking through a game, Berland and Lee suggested "code categories" that require computational thinking during a game of "Pandemic": "Conditional logic," "Algorithm building," "Debugging," "Simulation," and "Distributed computation" [144, p. 70].

Serious games inform players how well they are progressing towards predefined learning objectives. A game genre aiming to the development of skills transferable to the physical world is *simulation* training. However, less realistic serious games could involve transferable cognitive skills, such as conditional logic in decision-making. Due to their easy distribution and often low cost, digital games dominate the serious-gaming field. Kazimoglu et al. discuss what tasks were mapped to digital game activities for the development of skills related to computational thinking: "Problem identification and decomposition," "Creating efficient and repeatable patterns," "Practicing debug-mode," "Practicing run-time mode," and "Brainstorming" [21, p. 528].

Weintrop et al. "define constructionist video games as: Designed computational environments in which players construct personally meaningful artifacts to overcome artificial conflict or obstacles resulting in quantifiable outcomes" [145, p. 4]. The authors build games using the following three principles [145, pp. 5-6]:

> Principle 1: Constructionist video games include sufficiently expressive construction tools for players to engage with and build personally meaningful artifacts.
> Principle 2: Game goals and construction tools encourage exploration and discovery during play.
> Principle 3: Learners engage with and employ powerful ideas to advance through the game.

Commonly used visual programming environments for educational game development are:

1. Alice (https://www.alice.org/)
2. Blockly (https://developers.google.com/blockly/)
3. mBlock (http://www.mblock.cc/)
4. Scratch (https://scratch.mit.edu/)
5. ScratchJr (https://www.scratchjr.org/)

Bell and Bell discuss "ways to integrate computational thinking and music, and to show how arts can have a primary role in Computational Thinking learning" [146, p. 165]. The authors note that "the elements of music that define the scope of curriculum are often articulated as a list such as pitch, timbre, texture, dynamics, duration, tempo, and structure" [146, p. 153].

Programming musical expression depends on available programmable expressiveness, which includes coded structures that parameterize expression in some way. More broadly, music theory is knowledge on computational practices in sound organization, and music notation is a semiotic resource. Widmer and Goebl discuss computational models for musical expressiveness. The authors argue that “the purpose of computational models of expressive music performance is thus to specify precisely the physical parameters defining a performance (e.g., onset timing, inter-onset intervals, loudness levels, note durations, etc.)” [147, p. 204].

Music composition is essentially a process of computational thinking that aims to structure sound production around extemporized and conventional musical elements. For example, the development and use of antecedent and consequent musical sequences. Music theory is knowledge that comes from analyzing what was conventionalized through music composition in the past. New technology, such as virtual musical instruments and other ways of processing sound can lead to new conceptual ideas and thus the development of new music theory and novel ways of musical expression.

In the context of algorithmic music, Edwards argues “using algorithmic-composition techniques does not by necessity imply less compositional work or a shortcut to musical results; rather, it is a change of focus from note-to-note composition to a top-down formalization of compositional process [...] perhaps counterintuitively, such formalization of personal composition technique allows the composer to proceed from concrete musical or abstract formal ideas into realms hitherto unimagined, sometimes impossible to achieve through any other means than computer software” [148, p. 67]. Software that enables sound processing has been instrumental in creating new ways to compose music and use machines for musical expression. Commonly used visual programming environments for sound production are:

1. Audulus (http://audulus.com/)

2. Max (https://cycling74.com/products/max/)

3. OpenMusic (http://repmus.ircam.fr/openmusic/home)

4. Pd-L2Ork (http://l2ork.music.vt.edu/main/)

5. SynthEdit (https://www.synthedit.com/)

The following list presents a few concepts for the practice of algorithm design through musical computing:

- Sound Generator

  The computation of a sound signal. It can be a simple waveform such as the triangle and the square, or more complex via synthesis through the convolution of multiple waveforms and the use of digital filters.

- Sound Effect

  A sound effect is a transformation for aesthetic or other reasons. For example, artificial reverberation, pitch-harmonizing, and the equalization of sound are typical effects.

- Sound Sample

  A prerecorded sound can play forwardly or backwardly, slower or faster and with optionally transposed pitch.

- Musical Composition

  The organization of a musical sequence of orchestrated sound.

- Musical Instrument

  The use of an interface to control sound production via body gestures in real-time.

- Soundscape

  The creation sonic scenes representing purely real, blended (real-virtual), or purely virtual spaces.

- Spatialization

  The distribution and movement of sounds across an array of spatially distributed sound sources (such as loudspeakers or orchestral instruments of a large ensemble/orchestra).

- Display

  Sound can symbolize notifications such as alerts, progress, and events.

- Extemporization

  An unpremeditated musical sequence conceived on the spot.

2.3.5 Critique

Many researchers have not been providing explicit and detailed information on instructional design for the practice of computational thinking and their method of assessment. Such reports are necessary to enable meta-analyses and meaningful comparisons across studies. Lockwood and Mooney argue "problems such as defining Computational Thinking, disagreements on whether programming is an essential part of Computational Thinking, and whether Computational Thinking should be taught alongside pre-existing subjects, part of CS, or as a standalone module/course must be researched further [...] there are potential obstacles and difficulties when attempting to integrate Computational Thinking. These include a lack of trained teachers and potential difficulties with government policy or school administrators" [149, pp. 14-15].

Generally, the lack of consensus among scholars on the definition of computational thinking leads to a confusion around necessary components for practicing computational thinking. Paulson suggests that some definitions of computational thinking are so abstract or meaningless that "unless somebody can come up with a more insightful definition, it is indeed time to retire 'computational thinking'" [150, p. 8]. Defining meaningful social constructs is not a matter of external validity alone. Theories are valuable when they help people develop real-world applications.

Iversen et al. state that “Computational Thinking is a resourceful perspective for current societal challenges. Computational Thinking cannot, however, stand alone. It lacks a wider contextual approach to technological, cultural and societal challenges and change.” The authors suggest a “participatory agenda (PD) of computational empowerment” [151, pp. 3-4].

Biron is concerned that “the computational metaphor has so captured the imagination of some that they reject the present less-than-perfect world of the self and others for the perfect future world of the computer. The problem is exacerbated by the acceptance of the computational metaphor by many of those treating and educating these computer users and workers” [152, p. 111]. Computational thinking definitions should help educators design curricula, but Ruffini argues that it is a challenge to identify “objective metrics of conscious state” [153, p. 1].

Haseski et al. report that “multifarious definitions were attempted to explain the concept of Computational Thinking. However, it was determined that there was no consensus on this matter in the literature and several different concepts were mentioned in the definitions found in the literature” [154, p. 29]. While Grover and Pea report that “as computer science (CS) thunders its way into K-12 classrooms, lack of teachers to teach CS and pedagogically sound computing curricula remain significant challenges” [155, p. 1].

Román-González et al. point out that “in psychological terms, Computational Thinking is still a poorly defined construct, given that its nomological network has not been established yet.” The authors ask [156, p. 442]:

1. “Does Computational Thinking correlate with self-efficacy?”

2. “Does Computational Thinking correlate with personality?”

3. “What are the personality profiles of top and low computational thinkers?”

4. “How much variance of Computational Thinking can be explained by personality?”

Lastly, the authors model the following factors:

“cognitive”	“non-cognitive”
“Problem-solving ability”	“Computational Thinking self-efficacy”
“Reasoning ability”	“ICT self-efficacy”
“Spatial ability”	“Openness”
“Verbal ability”	“Conscientiousness”
“Numerical ability”	“Extraversion”
	“Agreeableness
	“Neuroticism”

where (ICT denotes *Information and Communication Technology*) [156, p. 456].

Shute et al. point out that “having no standard Computational Thinking assessment also makes it very difficult to compare results across various Computational Thinking studies” [157, p. 149]. However, Kalelioğlu et al. argue that “Computational Thinking literature is at an early stage of maturity and is far from either explaining what computational thinking is, or how to teach and assess this skill” [135, p. 584]. To be useful, definitions of computational thinking should specify how to practice it.

2.3.6 Proposed Nomological Network

Both a general definition and a systematic validation of the construct of computational thinking is needed to inform instructional design for its practice. Based on the literature review, this dissertation proposes a nomological network by describing antecedents, covariates, consequents, and similar constructs to computational thinking.

The most common context for teaching computational thinking is problem-solving. The following paragraphs discuss procedural steps of computational thinking, which are outlined in Table 1.

Table 1: A Procedural View of Computational Thinking.

Step	Task Description
1	Decompose the system into system-level functions (entities)
2	Codify the attributes of the system-level functions (attributes)
3	Specify how system-level functions relate to each other (relationships)
4	Design the system-level functions (functions)
5	Interconnect the system-level functions (inputs-outputs)

1: Decompose the system into system-level function

In the literature there is consensus among researchers that computational thinking skills include the ability to decompose convoluted situations and describe them as systems with distinct components. Computational thinking aims to describe the relations among these components and code them for processing by computers. Computations are regarded as entities with arithmetical and non-arithmetical attributes. Decomposition applies recursively to further characterize layers of abstraction. Each top-level abstraction can be regarded as a sub-system to be decomposed into a new layer of abstraction, so on and so forth. For example, a motor serves a specific function due to its location within a mechanical structure and some of its attributes are controllable. However, it is not necessary to understand the motor's inner workings in order to utilize its controllable attributes within a system.

2: Codify the attributes of the system-level functions

Once a situation has been described as a system, then the relations among system components could reveal systemic patterns. Once a pattern is identified, then it can be exploited, prevented, or enhanced. System components should be controllable in order to drive the system towards desired objectives. All the system functions and attributes intended to be accessible must be codified. Coding system functions and attributes takes into consideration existing constraints, desired objectives, and predefined computations.

3: Specify how system-level functions relate to each other

Abstraction helps specify computations on a level that is possible to codify relationships among system components. Specificity is attained when the relations among system components have been described with such detail that allows their coding within a programming framework. A computational network specifies how, and which components must communicate.

4: Design the system-level functions

Based on system-level attributes it is possible to develop rulesets for system operation including input internal or external to the system. In other words, to develop algorithms that automate system operation by performing specific computations when necessary. These algorithms can be evaluated for efficacy and efficiency based on known operational conditions.

5: Interconnect the system-level functions

A system may dynamically engage and disengage its components. Data structures describe which data operational algorithms can access and alter. Computational thinking is concerned with the automation, the scalability, and the controllability of the system: Automation leads to proven solutions by means of consistent replicability of solutions and services; Scalability optimizes the system's operation within dynamic situations, and controllability extends the applicability of a system among diverse environments.

Figure 1 presents the proposed nomological network for the construct of computational thinking.

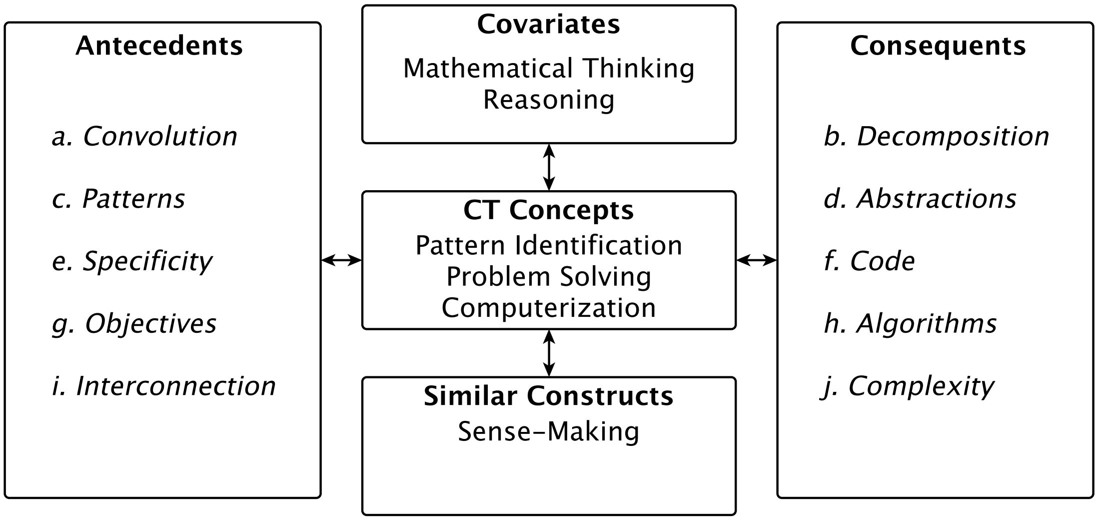


Figure 1: A Nomological Network for Computational Thinking.

2.4 Systems Design

2.4.1 Design Patterns for Self-Expression

What are helpful design patterns for self-expression? Arecchi defines *coherence*, *complexity*, and *creativity* [158, p.4]:

> Coherence = long range order (in space [vision] or time [music]);
> Complexity = display of different coherences;
> Creativity = jump from one coherence regime to another.

Variation is another helpful concept and is defined as a distinct difference between two similar structures. *Synchronicity* is defined by Lowry et. al. as "the degree to which a system enables a user to immediately respond to the system, and the degree to which the same system immediately responds to the user" [3, p. 17]. *Interactivity* is defined by Lowry et. al. as "the degree to which an interaction involving people (one-to-many) and systems (one-to-many) exhibits control, two-way communication, and synchronicity" [3, p. 16]. In the context of communication, a *cue* is defined by Green as "any feature of an entity that conveys information (including misinformation)" [159, p. 5]. Additionally, a *signal* is defined by Green as "any cue that was designed for its ability to convey the information that it does"

[159, p. 5].

2.4.2 Cognitive Mode

Kahneman describes a model of cognition that conceptualizes thinking into two systems labeled "intuition" and "reasoning." The first is "fast, parallel, automatic" and the second is "slow, serial, controlled" [79]. Reasoning is much more cognitively effortful than intuition is. Computational thinking is a process of reasoning, thus cognitively effortful, seeking to identify and computerize problem-solving. Although analytic thinking is a proven way to solve known problems, synthetic thinking is necessary to invent solutions to novel problems [160].

Yasar discusses both the analytic and the synthetic ways of thinking: "an iterative and cyclical process of deductive and inductive reasoning, as employed by scientists in research and students in learning, is the essence of computational thinking." This suggests that computational thinking is reasoning with the purpose of learning. Thinking is something we all do, but Yasar points out that not all of us do so "as methodologically, frequently, and consistently as scientists" [11]. Hsu et al. report that computational thinking literature includes the following "thinking steps:" "Abstraction," "Algorithm Design," "Automation," "Data Analysis," "Data Collection," "Data Representation," "Decomposition," "Parallelization," "Pattern Generalization," "Pattern Recognition," "Simulation," "Transformation," "Conditional logic," "Connection to other fields," "Visualization," "Debug & error detection," "Efficiency & performance," "Modeling," and "Problem solving" [138].

Sabitzer et al. used simple "entity-relationship diagrams" to conceptualize a system of computations [161]. The tree data type can be used to represent abstractions as virtual entities with inputs and outputs to visualize attributes, and virtual wires connecting outputs to inputs to visualize relationships [162]. For example, Figure 2 shows three basic trees of dataflow.

- A *sequential computation* begins with the root node and is a tree of relationships between nodes that are single-parents of their single-children;
- A *divergent computation* is a tree of relationships between the root node that is a single-parent to two or more children nodes (siblings) including their sequential sub-trees, and
- A *convergent computation* is a tree of relationships of two or more nodes including their sequential sub-trees that merge in the same single-child node (leaf).

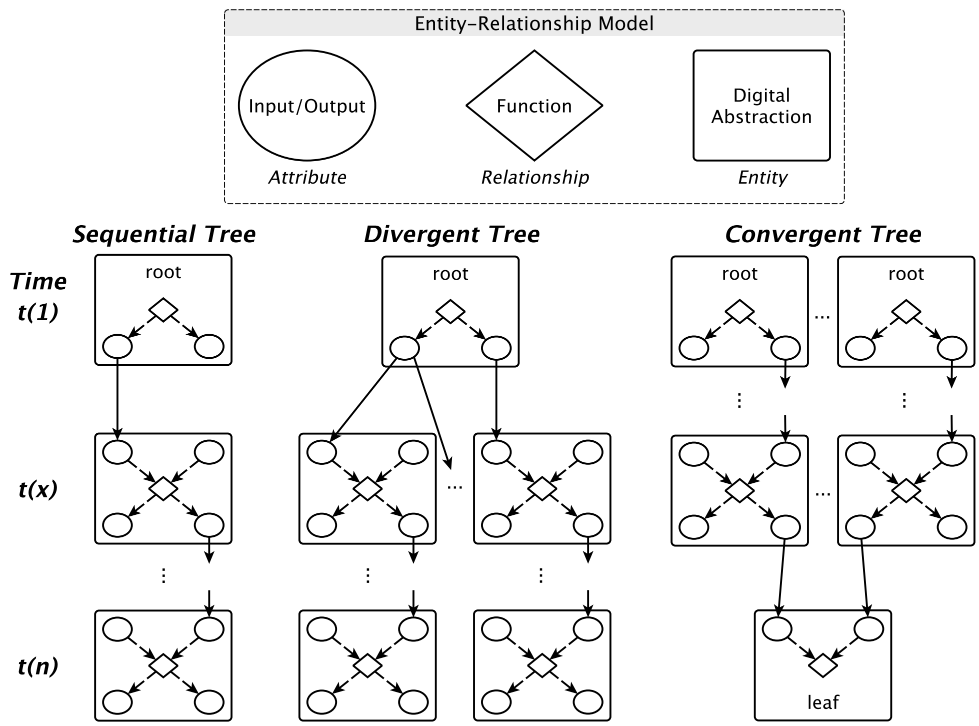


Figure 2: Basic Relational Trees of Dataflow Networks.

A multimodal system could utilize modes sequentially; use two or more modes to diverge from a multimode, or use two or more modes to converge on a multimode. Figure 3 shows three basic multi-mode patterns.

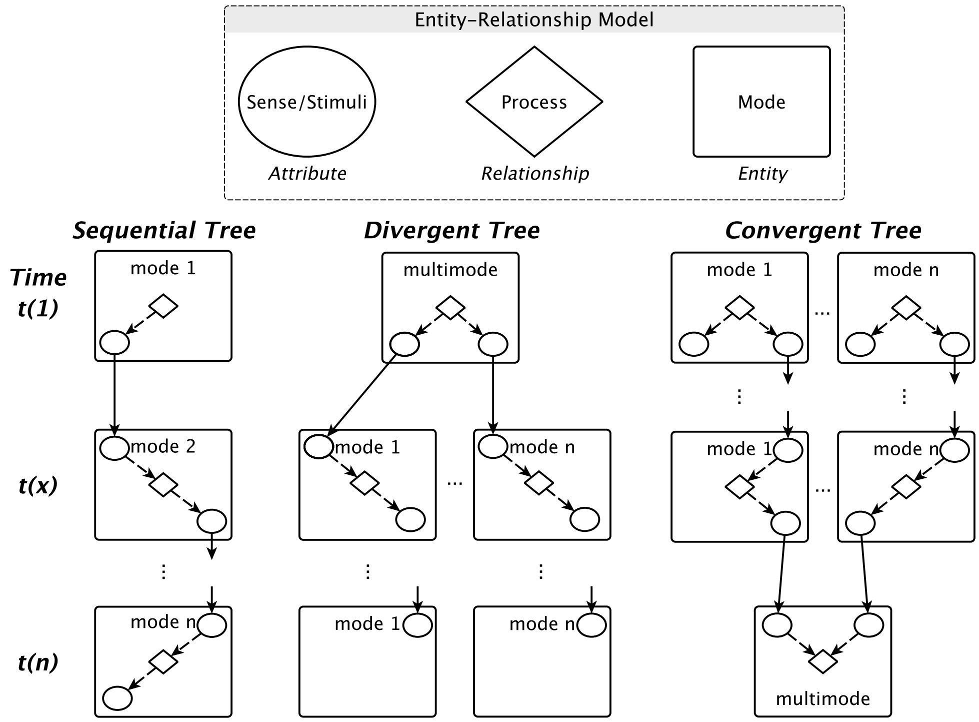


Figure 3: Basic Trees Representing Multimodality.

2.4.3 Affective Mode

The affective mode consists of the affective states of pleasure, arousal, and motivational salience. Berridge argues "many contemporary psychologists and affective neuroscientists do believe that affective reactions and emotions can occur unconsciously as implicit processes, as well as subjective feelings" [163, p. 2]. In other words, individuals may or may not be aware of why they feel more or less motivated to engage in an instructional activity.

Lang and Bradley found that hedonic tone can be communicated by simple picture compositions and thus argue that a delayed positive hedonic reaction to picture stimuli does not reflect "the complexity of information processing" [164, p. 442]. This dissertation presumes that the same holds for music stimuli. Musical expression has an impact on an individual's affective states both due the external auditory stimuli and the internal cognitive awareness of having some control over the perceived sound's production. It is hypothesized that during instructional activities, increased pleasure and arousal are associated to increased motivational salience.

2.4.4 Behavioral Mode

Five prominent factors that drive behavior are the actor's capability, incentive, physical constraints, habits, and the importance of behavior [165]. The capability of individuals in designing and controlling sound signals varies and is not expected. An instructional physical or virtual manipulative offers simple sound production affordances to aid in computational thinking. The behavioral mode appeals to self-expression through musical expression. Thus, individuals must practice some computational thinking to engage in musical expression. Computational knowledge is developed by programming and applying cues that result in musical expression.

Figure 4 shows the proposed affective model for the practice of computational knowledge.

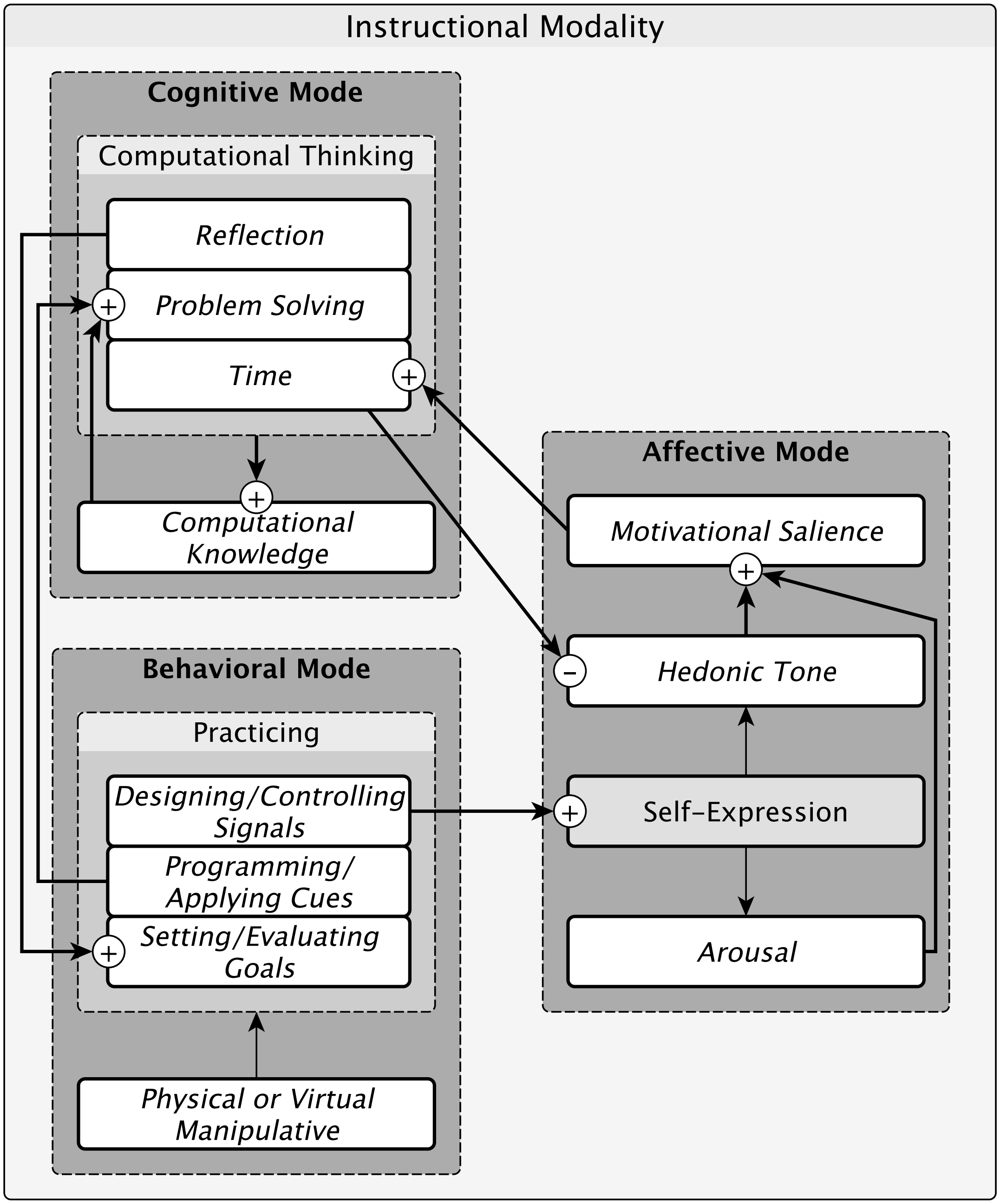


Figure 4: An Affective Model for the Practice of Computational Thinking through Self-Expression.

2.4.5 Assessment of levels of Knowledge and Thinking

Prior knowledge can be explicit or tacit. The first could be expressed analytically, while the latter manifests in practice. When predefined, levels of knowledge and thinking can be assessed before, during, and after instructional activities. To exemplify, a set of computational questions assessing predefined levels of thinking and knowledge on the subject of interval scale were developed based on “a revised Bloom’s taxonomy” [80]. The taxonomy consists of six levels on its “cognitive process dimension” (thinking), and of four levels on its “knowledge” dimension [80, 166]. This taxonomy is also mapped onto four areas of complexity: *functionality*, *optimality*, *feasibility*, and *practicality*.

In the context of instructional activities, Krathwohl argues that Bloom’s revised “taxonomy table can also be used to classify the instructional and learning activities used to achieve the objectives, as well as the assessments employed to determine how well the objectives were mastered by the students” [80, p. 217]. Table 2 describes the proposed assessment matrix $\mathcal{A}$, $\forall a \in [0, 1]$.

Table 2: A Diagnostic-Formative-Summative Assessment Matrix.

	Fact	**Concept**	**Procedure**	**Strategy**
	Functionality		***Feasibility***	
Remembering	$1(a_{1,1}+0)$	$2(a_{1,2}+0)$	$3(a_{1,3}+0)$	$4(a_{1,4}+0)$
Understanding	$1(a_{2,1}+1)$	$2(a_{2,2}+1)$	$3(a_{2,3}+1)$	$4(a_{2,4}+1)$
Applying	$1(a_{3,1}+2)$	$2(a_{3,2}+2)$	$3(a_{3,3}+2)$	$4(a_{3,4}+2)$
	Optimality		***Practicality***	
Analyzing	$1(a_{4,1}+3)$	$2(a_{4,2}+3)$	$3(a_{4,3}+3)$	$4(a_{4,4}+3)$
Evaluating	$1(a_{5,1}+4)$	$2(a_{5,2}+4)$	$3(a_{5,3}+4)$	$4(a_{5,4}+4)$
Creating	$1(a_{6,1}+5)$	$2(a_{6,2}+5)$	$3(a_{6,3}+5)$	$4(a_{6,4}+5)$

In Table 2, the optimality quartile focuses on ways of increasing application optimality. It is concerned with conceptual differentiation, the selection of optimality criteria, and the design of optimal solutions. The feasibility quartile focuses on analytic design skills. It is concerned with standardized procedures, the interpretation of empirical data, and application appropriateness. The practicality quartile focuses on synthetic design skills. It is concerned with the creation of practical and novel solutions. The functionality quartile focuses on conceptual design. It is concerned with applying operating principles for the development of procedures.

Table 3 shows a generalized assessment matrix for levels of skill and knowledge $\hat{\mathcal{A}}$, $\forall \hat{a} \in [0, 1]$, where ω is a constant offset attributed to each skill.

Table 3: Generalized Diagnostic-Formative-Summative Assessment Matrix.

Skill	**Knowledge**			
	Label k_1	Label k_2	$\dots$	Label k_m
Label l_1	$1(\hat{a}_{1,1} + 0)$	$2(\hat{a}_{1,2} + 0)$	$\dots$	$m(\hat{a}_{1,m} + 0)$
Label l_2	$1(\hat{a}_{2,1} + \omega_1)$	$2(\hat{a}_{2,2} + 1)$	$\dots$	$m(\hat{a}_{2,m} + 1)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Label l_n	$1(\hat{a}_{n,1} + \omega_n)$	$2(\hat{a}_{n,2} + n)$	$\dots$	$m(\hat{a}_{n,m} + 1)$

2.5 Propositions

This dissertation investigates the affective states in visual and musical modalities of four distinct instructional activities to evaluate the following three propositions: P_1, P_2, and P_3.

- P_1*: Computational Knowledge* after instructional activities with similar but distinct modalities of computational thinking practice will be inversely proportional to the cognitive effort difference between activities.

The first proposition (P_1) postulates that the difference in cognitive effort between similar but distinct modalities of computational thinking practice will have an impact on the difference of computational knowledge measurements between before and after an instructional activity. Green informs us that "self-expression is as sensitive to how an action is carried out as it is to which action is carried out" [159, p. 45].

A well-documented effect, the *distributed practice effect*, posits that distributing the effort of reasoning in sequential activities will increase learning during the overall instructional session [167]. Meaning that the least effortful learning modality will be associated with the highest gain in computational knowledge.

Mentally challenging instructional activities that evoke relevant prior knowledge increase the chances for a deeper understanding of their learning content [168]. However, distributing cognitive breaks within instructional activities is critical for individuals' affective states.

- P_2*:* Individuals' more positive affective states of pleasure and arousal after than before an instructional activity will be associated with stronger motivational salience during the activity.

The second proposition (P_2) postulates a positive association of individuals' motivational salience during an instructional activity with their self-reported hedonic usability of the activity. Motivational salience is sensitive to how pleasurable an activity is to the learner.

Engaging in an instructional activity is a goal-oriented behavior. Instructional activities should communicate goals clearly to invoke goal-oriented behavior. Also, instructional systems should avoid overburdening users with choices. Iyengar and Lepper provide evidence that unlimited choices may have negative consequences for motivational salience [169]. One way of doing so is hiding extra choices until users explicitly seek for more choices. Monitoring individuals' affect during instructional activities would reveal which learning modalities are more engaging for each individual.

- P_3*:* Stronger motivational salience during computational thinking practice will be associated with longer periods of practice.

The third proposition (P_3) postulates that motivational salience will differ between distinct learning modalities. This dissertation proposes an affective model of cognitive practice through self-expression. The validation of the suggested model will inform multimodal design theory on the role of learners' affective states in instructional activities centered around self-expression.

3 Research Design & Methodology

3.1 Introduction

This study aims to investigate four distinct learning modalities for the practice of computational thinking. It utilizes a pretest-posttest design that is appropriate for a mix of within-subjects and between-subjects comparisons. Based on existing literature, non-cognitive co-variates relevant to computational thinking practice include the big five personality traits, core-affect, gender, and age [156]. Study participants are randomly assigned one of four distinct learning modalities during treatment. The four learning modalities are:

1. Computational Thinking - operationalized by a visual programming activity;
2. Computational Thinking for sound production - operationalized by a visual programming for sound production activity;
3. Computational Thinking for multimodal sound production - operationalized by a visual programming for sound production including a virtual musical instrument activity, and
4. Cognitive break - operationalized by watching an audiovisual excerpt of oceanic scenery.

3.2 Design

3.2.1 Operationalization of Cognitive Mode

A measure of computational knowledge based on the concept of the *interval scale* is mapped onto levels of thinking and knowledge. Table 4 shows an assessment map for levels of thinking and knowledge based on Bloom's revised taxonomy [80].

Table 4: Assessment Matrix Pertaining to the *Interval Scale.*

	Fact	Concept	Procedure	Strategy
	Functionality		***Feasibility***	
Remembers	What is an interval	What is an interval scale	How to create an interval scale	When to use an interval scale
Understands	Why interval scale units are arbitrary and sensitivity is definite	Why ratios based on an interval scale are arbitrary	How to change an interval scale's sensitivity	When to alter an interval scale
Applies	An interval scale in a given context	An alteration of an interval scale in a given context	Pattern recognition based on an interval scale in a given context	Statistics of an applied interval scale
	Optimality		***Practicality***	
Analyzes	An interval scale in a given context	The discretization of a phenomenon based on an applied interval scale	The appropriateness of an interval scale in a given context	The practicality of an applied interval scale
Evaluates	The optimality of an interval scale in a given context	Optimality constraints of an applied interval scale	The practicality of an interval scale in a given context	Practicality constraints of an applied interval scale
Creates	An optimal interval scale in a given context	Optimality criteria for the application of an interval scale	A practical interval scale in a given context	Practicality criteria for the application of an interval scale

3.2.2 Operationalization of Affective Mode

The affective mode presumes participants' self-expression during treatments, which are accessed via internet browser. Study participants are given predefined visual programming algorithm.

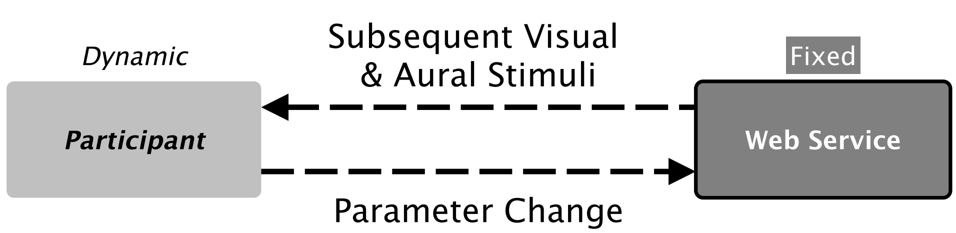


Figure 5: A Self-Regulated Artificial Coupling for Expression.

3.2.3 Operationalization of Behavioral Mode

This study expects participants to control signals and cues based on available semiotic resources. Table 5 shows inter-semiotic relationships between the semiotic resources found in each of the distinct learning.

Table 5: *Semiotic Resources:* Inter-semiotic Relationships.

<table>
<tr><td colspan="3">Visual Programming</td><td colspan="2"></td></tr>
<tr><td colspan="4">Visual Programming for Sound Production</td><td></td></tr>
<tr><td colspan="5">Visual Programming for Sound Production including a Virtual Musical Instrument</td></tr>
<tr><td>Computational</td><td>Arithmetical</td><td>Graphical</td><td>Auditory</td><td>Virtual</td></tr>
<tr><td>Discreteness</td><td>Vector</td><td>MIDI-pitch</td><td>Pitch</td><td>Metal-bar location</td></tr>
<tr><td>Controllability</td><td>Scalar</td><td>Sound volume</td><td>Loudness</td><td>Solenoid strike</td></tr>
<tr><td>Quantization</td><td>Logarithmic</td><td>Digital tempo</td><td>Rhythm</td><td>Motor position</td></tr>
<tr><td>Conditionality</td><td>Discrete</td><td>Virtual abstractions</td><td>Timbre</td><td>Strike repetition</td></tr>
<tr><td>Aggregation</td><td>Continuous</td><td>Dataflow</td><td>Polyphony</td><td>Monophonic</td></tr>
</table>

3.3 The Device

A web service was developed for online access via internet browser and preferably on computers with a touch-screen. The web service features three distinct instructional activities. Server-side languages (PHP, Python, Shell Scripting) prepare the instructional content that is administered by a web server over an internet to participants' internet browsers. Client-side languages (HTML5, CSS, JavaScript) create a dynamic visual programming environment, which can connect to a programmable virtual musical instrument via WebSocket communication [170, 171]. Figures 6 and 7 show the visual programming environment and the virtual musical instrument respectively. The dynamic visual programming environment imitates the proven PD-L2Ork programming environment [7, 172, 8].

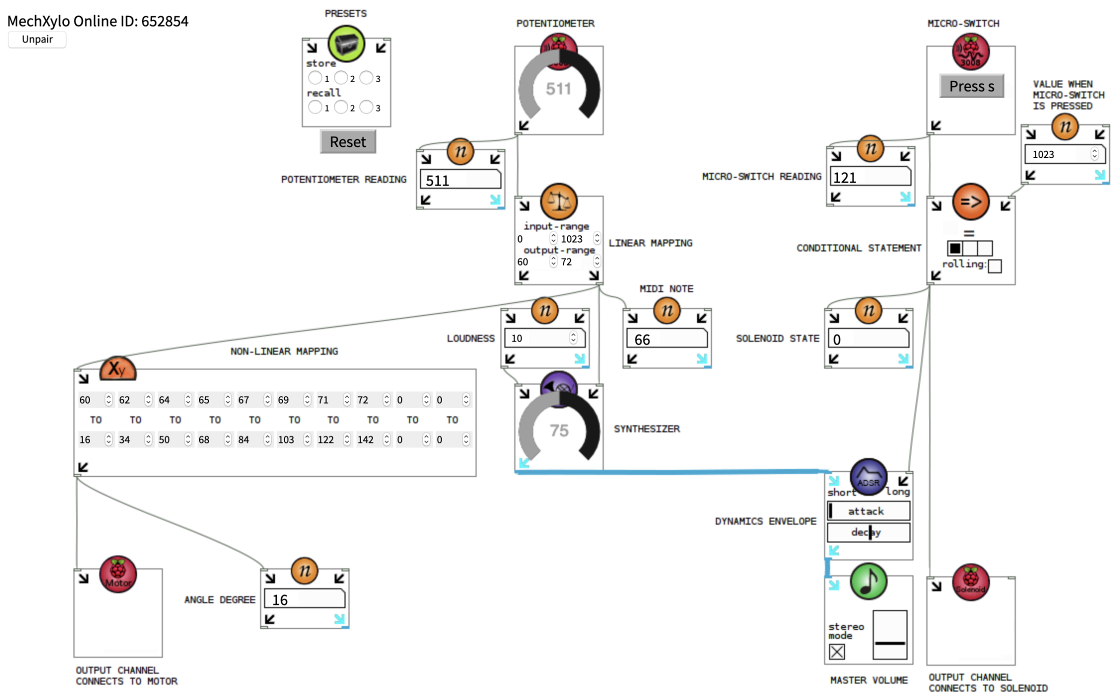


Figure 6: Web-based Computing - Visual Programming.

Figure 7: Web-based Computing - Programmable Virtual Musical Instrument.

3.4 Protocol

The experimental research design is based on repeated and covariance measures within-subjects, and on distinct treatments between-subjects. Figure 8 presents the steps of the study's pre-test post-test experimental protocol.

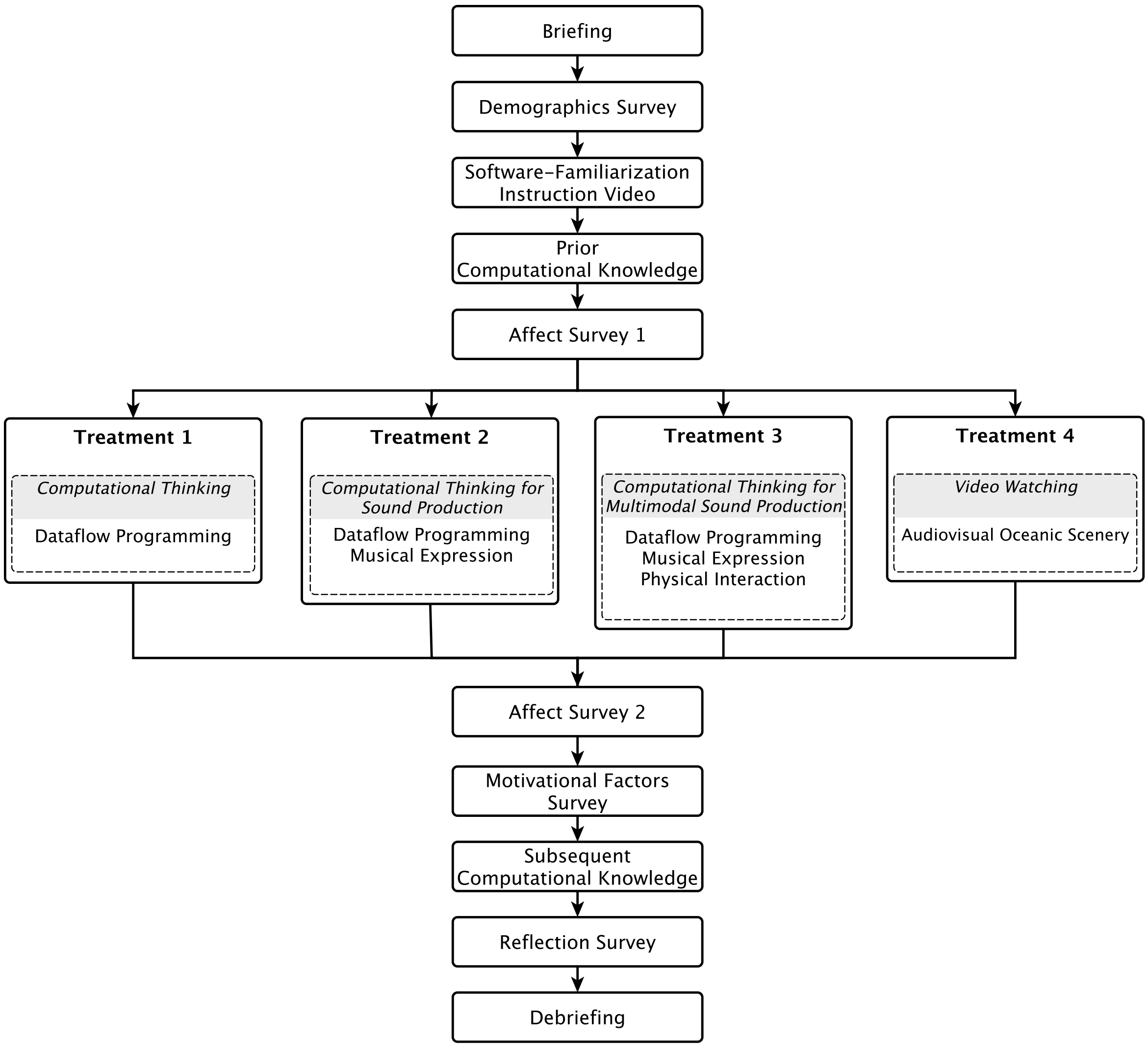


Figure 8: A Mixed Factorial Experimental Design. Descriptions of the steps are available in Appendix A, Section 6.2.

There are three groups of predefined hypotheses:

- **H1.* - Null Hypotheses for *Computational-Knowledge*:**

H1.1 Treatment 1 will not be associated with a significant difference between *Subsequent-Computational-Knowledge* and *Prior-Computational-Knowledge*.

H1.2 Treatment 2 will not be associated with a significant difference between *Subsequent-Computational-Knowledge* and *Prior-Computational-Knowledge*.

H1.3 Treatment 3 will not be associated with a significant difference between *Subsequent-Computational-Knowledge* and *Prior-Computational-Knowledge*.

H1.4 Treatment 4 will not be associated with a significant difference between *Subsequent-Computational-Knowledge* and *Prior-Computational-Knowledge*.

H1.5 The difference between *Subsequent-Computational-Knowledge* and *Prior-Computational-Knowledge* of Treatment 4 will not be associated with a significant dissimilarity between the same difference in other treatments.

- **H2.* - Null Hypotheses for affective states *Pleasure* and *Arousal*:**

H2.1 Treatment 1 will not be associated with a significant difference in the *State-of-Pleasure* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.2 Treatment 1 will not be associated with a significant difference in the *State-of-Arousal* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.3 Treatment 2 will not be associated with a significant difference in the *State-of-Pleasure* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.4 Treatment 2 will not be associated with a significant difference in the *State-of-Arousal* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.5 Treatment 3 will not be associated with a significant difference in the *State-of-Pleasure* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.6 Treatment 3 will not be associated with a significant difference in the *State-of-Arousal* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.7 Treatment 4 will not be associated with a significant difference in the *State-of-Pleasure* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.8 Treatment 4 will not be associated with a significant difference in the *State-of-Arousal* between *Affect-Survey-1* and *Affect-Survey-2*.

H2.9 The difference in the *State-of-Pleasure* between *Affect-Survey-2* and *Affect-Survey-1* of Treatment 4 will not be associated with a significant dissimilarity when compared to the same difference in other treatments.

H2.10 The difference in the *State-of-Arousal* between *Affect-Survey-2* and *Affect-Survey-1* of Treatment 4 will not be associated with a significant dissimilarity when compared to the same difference in other treatments.

- **H3.* - Null Hypotheses for motivational factors *Empowerment*, *Usefulness*, *Success*, and *Interest*:**

H3.1 Treatment 4 will not be associated with a significant decrease in salience of affective *Motivational-Empowerment* than other treatments.

H3.2 Treatment 4 will not be associated with significant decrease in salience of affective *Motivational-Usefulness* than other treatments.

H3.3 Treatment 4 will not be associated with significant decrease in salience of affective *Motivational-Success* than other treatments.

H3.4 Treatment 4 will not be associated with significant decrease in salience of affective *Motivational-Interest* than other treatments.

3.4.1 Sample

Sample size (N) calculation:

$$N = \frac{2(Z_\alpha + Z_{1-\beta})^2\sigma^2}{\Delta^2} = \frac{2(1.65 + 1.0364)^2(\frac{1.88}{12})^2}{(\frac{1}{12})^2} \simeq 51 \quad (1)$$

where Z_α is a constant for one-tail effect with 5% type I error;
$Z_{1-\beta}$ is a standardized constant for power 80%;
σ is the maximum anticipated standard deviation; and
Δ the difference in effect among groups (between pre and post treatment means) or between group means.

Depending on the standard deviation of the conceptualized dependent variables, a sample between 100 and 200 subjects should be sufficient for investigating statistically significant differences within and between groups. Subjects in the sample will be distributed randomly and evenly to each treatment group.

Common study related biases were suppressed as follows:

1. The *group assignment bias* was limited by randomized group assignment.
2. The *observer-expectancy bias* was eliminated via the online automated administration of study sessions.
3. The *subject-expectancy bias* was eliminated by keeping subjects unaware of hypothesized effects.

3.5 Measures

3.5.1 Measure of Computational Knowledge

A 24-item Computational Knowledge (CK) scale was developed for the subject of *interval scale*. The scale was tested and validated by a relevant study that showed it can be split into two, statistically equivalent, 12-item subscales [$t(30) = -.65$; $p = .518$]. In the validation study, the correlation of the Prior-CK subscale with the CK scale was .95 ($p < .0001$), and the correlation of the Subsequent-CK subscale with the CK scale was .94 ($p < .0001$). The quiz questions for the Prior-CK and Subsequent-CK subscales are described in Appendix A, sections 6.2.1 and 6.2.2, respectively.

3.5.2 Measure of Core-Affect (Enjoyment & Excitement)

The affective states of Pleasure (Enjoyment) and Arousal (Excitement) are measured by two affective sliders in the range of -1 to 1. [173]. Figure 9 shows a graphical representation of the sliders.

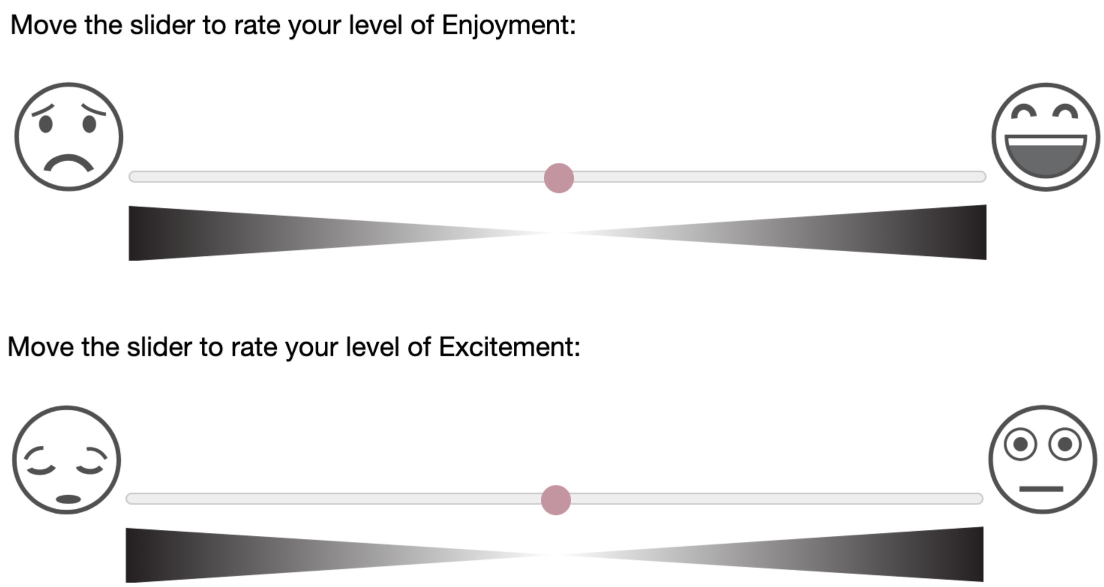


Figure 9: Affective Sliders for Self-Reported Enjoyment and Excitement [173].

3.5.3 Measure of Motivational Salience

Motivational Salience is measured by a four-factor scale in accordance with Jones' "MUSIC model of academic motivation," which includes five factors [174, 73]. The *Caring* factor does not apply to an automated instructional activity and it was not included in this study. The scales for the four motivational factors Empowerment, Usefulness, Success, and Interest are described in Appendix A, Section 6.2.

3.6 Hypotheses Testing

In the hypotheses group H1.*, the conceptualized dependent variable (DV) is *Subsequent Computational Knowledge*. The general null hypothesis is that Subsequent-CK mean measured after treatment, adjusted for covariance of *Prior Computational Knowledge*, the covariate (C), measured before treatment, does not differ significantly between the four *Treatment Groups*, an independent variable (IV). Thus, for such hypotheses an analysis of covariance (ANCOVA) will be performed to determine differences, while adjusting the mean of *Subsequent Computational Knowledge* to what it would have been if there was no variability in *Prior Computational Knowledge*. The interaction IV $\times$ C will be included as a predictor in a linear regression to check the following assumptions: 1) the residual variability should be normally distributed, 2) the covariance between the DV and the C is linear, 3) the interaction IV $\times$ C is not significant at the type I error level. If the previous assumptions do not hold, then a multivariate analysis of variance (MANOVA) will be performed instead.

Table 6: ANCOVA Summary.

Variation	SS	DF	MS	F
Between Treatments	$\mathrm{SS}_b = \dfrac{\sum_{i=1}^{g} O_i^2}{n_g} - \dfrac{O^2}{N}$	$g-1$	$\dfrac{\mathrm{SS}_b}{\mathrm{DF}_b}$	
Covariate	$\mathrm{SS}_c = \dfrac{O_i^2}{n_g} - \dfrac{O^2}{N}$	1	$\dfrac{\mathrm{SS}_c}{\mathrm{DF}_c}$	$\dfrac{\mathrm{MS}_c}{\mathrm{MS}_e}$
Within Subjects	$\mathrm{SS}_e = \sum_{k=1}^{N} o_k^2 - \dfrac{\sum_{i=1}^{g} O_i^2}{n_g}$	$N-g$	$\dfrac{\mathrm{SS}_e}{\mathrm{DF}_e}$	
Total	$\mathrm{SS}_T = \mathrm{SS}_b + \mathrm{SS}_c + \mathrm{SS}_e$	$N-1$		

where SS is the sum of squares;
DF is the degrees of freedom;
MS is the mean of the squares;
F is the statistical test $F(\mathrm{DF_b}, \mathrm{DF_W})$;
b, W, o, e, and T are indexes pointing to the source of variation for the descriptive statistics (column SS is specified - columns DF, MS, and F are implied);
i, j, and k, and l are indexes of enumeration;
g is an index of the experimental treatment group;
n_g is the number of observation sources (Subjects) in the sample per each treatment g;

O_i is the sum of observations per each treatment g, and $O_i := \sum_{j=1}^{n_g} o_j$;
o_j is the individual source of observation (Subject) per each treatment g;
O is the total sum of observations, and $O := \sum_{k=1}^{N} o_k$;
o_k is the individual observation.

In the hypotheses group H2.*, the conceptualized dependent variable, measured repeatedly, is affective *Pleasure-Arousal* (DV). The general null hypothesis is that a change in the affective *Pleasure-Arousal* mean between a before- and an after-treatment repeated measurement will not differ significantly among the four *Treatment Groups*, an independent variable (IV). Thus, for such hypotheses a repeated-measures analysis of variance (RM-ANOVA) will be performed to determine differences, while reducing the variability due to within-subjects random error.

Table 7: Repeated Measures ANOVA Summary per Treatment.

Variation	SS	DF	MS	F
Between Repeats	$\mathrm{SS}_b = \frac{\sum_{i=1}^{n_r} O_i^2}{n_g} - \frac{O_g^2}{N_g}$	$n_r - 1$	$\frac{\mathrm{SS}_b}{\mathrm{DF}_b}$	$\frac{\mathrm{MS}_b}{\mathrm{MS}_e}$
Within Treatment:	$\mathrm{SS}_W = \sum_{k=1}^{N_g} o_k^2 - \frac{\sum_{i=1}^{n_r} O_i^2}{n_g}$	$N_g - n_r$	$\frac{\mathrm{SS}_b}{\mathrm{DF}_b}$	
- Subjects	$\mathrm{SS}_o = \frac{\sum_{l=1}^{n_g} O_l^2}{n_r} - \frac{O_g^2}{N_g}$	$n_g - 1$	$\frac{\mathrm{SS}_o}{\mathrm{DF}_o}$	
- Error	$\mathrm{SS}_e = \mathrm{SS}_W - \mathrm{SS}_o$	$N_g - n_r - n_g + 1$	$\frac{\mathrm{SS}_e}{\mathrm{DF}_e}$	
Total of Treatment	$\mathrm{SS}_T = \mathrm{SS}_b + \mathrm{SS}_W$	$N_g - 1$		

where SS is the sum of squares;
DF is the degrees of freedom;
MS is the mean of the squares;
F is the statistical test $F(\mathrm{DF_b}, \mathrm{DF_W})$;
b, W, o, e, and T are indexes pointing to the source of variation for the descriptive statistics (column SS is specified - columns DF, MS, and F are implied);
i, j, k, and l are indexes of enumeration;
g is an index of the experimental treatment group;
n_r is the number of times a measurement has been repeated per source of observation (Sub-

ject) o_j;
n_g is the number of observation sources (Subjects) in the sample per each different treatment g;
N_g is the total number of observations per each treatment g;
O_i is the sum of observations per each different time of measurement, and $O_i := \sum_{j=1}^{n_g} o_j$;
o_j is the individual source of observation (Subject) per each different treatment g;
O_g is the total sum of observations per each treatment g, and $O_g := \sum_{k=1}^{N_g} o_k$;
o_k is the individual observation per each treatment g;
O_l is the sum of observations per each different source of observation (Subject) o_j, and $O_l := \sum_{m=1}^{n_r} o_m$;
o_m is the individual observation per each different source of observation (Subject) o_j.

In the hypothesis group H3.*, the conceptualized dependent variable, measured after treatment, is *Motivational Salience* (DV). The general null hypothesis is that *Motivational Salience* mean will not differ significantly between the four *Treatment Groups*, an independent variable (IV). Thus, for such hypotheses, an analysis of variance (ANOVA) will be performed to determine differences between treatments.

Table 8: ANOVA Summary.

Source of Variation	SS	DF	MS	F
Between Treatments	$\mathrm{SS}_b = \frac{\sum_{i=1}^{g} O_i^2}{N_g} - \frac{O^2}{N}$	$g-1$	$\frac{\mathrm{SS}_b}{\mathrm{DF}_b}$	$\frac{\mathrm{MS}_b}{\mathrm{MS}_e}$
Within Subjects	$\mathrm{SS}_W = \sum_{k=1}^{N} o_k^2 - \frac{\sum_{i=1}^{g} O_i^2}{N_g}$	$N-g$	$\frac{\mathrm{SS}_b}{\mathrm{DF}_b}$	
Total	$\mathrm{SS}_T = \mathrm{SS}_b + \mathrm{SS}_e$	$N-1$		

where SS is the sum of squares;
DF is the degrees of freedom;
MS is the mean of the squares;
F is the statistical test $F(\mathrm{DF_b}, \mathrm{DF_W})$;
b, W, e, and T are indexes pointing to the source of variation for the descriptive statistics (column SS is specified - columns DF, MS, and F are implied);

i, j, and k are indexes of enumeration;
g is an index of the experimental treatment group;
N_g is the total number of observation sources (subjects) per each treatment g;
N is the total number of observations;
O_i is the sum of observations per each different time of measurement, and $O_i := \sum_{j=1}^{N_g} o_j$;
o_j is the individual observation per each treatment g;
O is the sum of observations, and $O := \sum_{k=1}^{N} o_k$;
o_k is the individual observation.

3.7 Inferential Statistics

A sentiment analysis of the textual feedback from subjects will be performed [175, 176, 177]. Additionally, a word cloud will be constructed with terms that appear a minimum of 4 times [178].

The effect size of the difference between Prior and Subsequent Computational Knowledge will be estimated by adjusting the Prior Computational Knowledge mean of each treatment to the average of all four treatments before subtracting it from the after-treatment mean.

$$\Delta M_g = \bar{M}^{\text{pre}} - M_g^{\text{post}} \quad , \quad g \in \{1, 2, 3, 4\}, \tag{2}$$

where g is the treatment group; ΔM_g is the difference between Prior and Subsequent Computational Knowledge of the group g; $\bar{M}^{\text{pre}}$ is the average Prior Computational Knowledge of all treatment groups, and M_g^{post} is the Subsequent Computational Knowledge of each group g.

The pooling of subjects based on predefined characteristics will enable a probability estimation of predefined characteristics per each treatment group.

$$P_g \simeq \frac{N_g^{\text{pool}}}{N_g^{\text{total}}} \quad , \quad g \in \{1, 2, 3, 4\}, \tag{3}$$

where g is the treatment group; N_g^{pool} is the number of observations in a group g subset, and N_g^{total} is the number of the observations in all of group g ($N_g^{\text{pool}} \subseteq N_g^{\text{total}}$).

4 Data Analysis

4.1 Descriptive Statistics

The study was advertised via social media, email lists, and email, both within and outside Virginia Tech. Data from a sample of 146 subjects was collected. Duplicate and automated *bot-like* responses (identified via participant IP addresses, participation time, and/or repetition of the same answer in multiple different questions) were removed from the data to ensure quality; these duplicate and automated responses had repetitive, non-relevant, and out of range answers. Also, participants who did not complete more than 80% of the survey were excluded from the sample because there was too much missing data in their responses. The final sample of 120 participants was imported to SAS statistical software to be analyzed [179], used for hypotheses testing, and for exploratory research. Missing data in the final sample were left missing. However, some missing data (specifically, excitement and enjoyment) were inferred to be the same to participants' previous ratings when their rating was left unchanged during repeated measurements. The sample's demographics are summarized in tables 9, and 10.

Table 9: Sample Demographics - Age

Age	**Count**	**%**
18-25	63	52.5
26-35	39	32.5
36-45	7	5.8
46+	2	1.7
Missing	9	7.5
Total	**120**	**100.0**

Table 10: Sample Demographics - Gender

Tre	Gender	Count	%	Age
1	Female	15	50.0	
1	Male	15	50.0	
1	Non Binary	0	0.0	
1	Missing	0	0.0	
1	Sum	30	100.0	26
2	Female	11	36.7	
2	Male	17	56.7	
2	Non Binary	1	3.3	
2	Missing	1	3.3	
2	Sum	30	100.0	26
3	Female	17	56.7	
3	Male	12	40.0	
3	Non Binary	1	3.3	
3	Missing	0	0.0	
3	Sum	30	100.0	26
4	Female	17	56.7	
4	Male	12	40.0	
4	Non Binary	1	3.3	
4	Missing	0	0.0	
4	Sum	30	100.0	29
Total	Female	60	50.0	
Total	Male	56	46.7	
Total	Non Binary	3	2.5	
Total	Missing	1	0.8	
Total	**Sum**	**120**	**100.0**	

Note: Tre= Treatment (4 is the control treatment); Age= Mean age in years.

Table 11 contains descriptive statistics for the three dependent variables 1) Computational Knowledge, 2) Core-Affect (Enjoyment & Excitement), and 3) Motivational Salience (Empowerment, Usefulness, Success, Interest), plus indexes of personality traits, the Big Five Inventory, in which: Agreeableness measures being respectful and trustful in others; Conscientiousness measures being responsible and productive; Extroversion measures being sociable and assertive; Neuroticism measures being inclined to anxiety and dejection, and Openness-to-experience measures being inclined to curiosity and creativity.

Table 11: Sample Descriptive Statistics

Groups		*Comp/nal Knowledge*				*Core-Affect*						*Motivational Factors*				*Big-Five Inventory*				
T	**Stat**	**CK**	**Pre**	**Post**	$\Delta_{\mathbf{CK}}$	$\mathbf{Enj_1}$	$\mathbf{Enj_2}$	$\Delta_{\mathbf{Enj}}$	$\mathbf{Exc_1}$	$\mathbf{Exc_2}$	$\Delta_{\mathbf{Exc}}$	$\mathbf{M_E}$	$\mathbf{M_U}$	$\mathbf{M_S}$	$\mathbf{M_I}$	$\mathbf{T_A}$	$\mathbf{T_C}$	$\mathbf{T_E}$	$\mathbf{T_N}$	$\mathbf{T_O}$
1	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
1	MIN	.174	.139	.167		0.000	0.000		0.000	0.000		.167	.167	.167	.168	.338	.289	.082	.087	.407
1	MAX	.849	.917	.950		.950	1.000		1.000	1.000		1.000	.967	1.000	1.000	.680	.761	.691	.598	.764
1	MEAN	.560	.540	.579	.039	.383	.413	.031	.435	.371	-.064	.641	.422	.557	.522	.535	.561	.420	.409	.586
1	STD	.193	.222	.203		.300	.312		.322	.316		.210	.228	.255	.233	.089	.128	.157	.132	.097
2	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
2	MIN	.231	.139	.194		0.000	0.000		0.000	0.000		.167	.167	.167	.222	.395	.313	.202	.142	.369
2	MAX	.824	.833	.883		1.000	1.000		1.000	1.000		.887	.956	.843	.926	.743	.778	.782	.684	.800
2	MEAN	.575	.550	.599	.049	.485	.504	.020	.550	.421	-.129	.587	.471	.579	.574	.583	.546	.412	.407	.568
2	STD	.159	.180	.183		.293	.308		.295	.287		.189	.243	.177	.193	.088	.111	.142	.145	.129
3	N	30	30	30		30	30		30	30		29	30	30	30	30	30	30	30	30
3	MIN	.274	.222	.297		0.000	0.000		0.000	0.000		.168	.167	.167	.167	.128	.330	.084	.181	.306
3	MAX	.882	.992	.917		.905	1.000		1.000	1.000		.945	.723	.838	.901	.683	.800	.778	.708	.778
3	MEAN	.604	.603	.605	.002	.373	.369	-.003	.408	.331	-.078	.575	.346	.473	.447	.520	.568	.437	.420	.578
3	STD	.154	.187	.162		.285	.305		.311	.304		.204	.178	.237	.201	.127	.127	.167	.136	.126
4	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
4	MIN	.194	.139	.250		0.000	.105		0.000	0.000		.248	.213	.268	.268	.338	.290	.033	.160	.206
4	MAX	.888	.917	.883		1.000	1.000		1.000	1.000		1.000	.862	1.000	.920	.757	.786	.754	.711	.744
4	MEAN	.557	.521	.593	.072	.418	.558	.140	.505	.450	-.055	.596	.453	.668	.586	.571	.531	.412	.431	.549
4	STD	.169	.205	.168		.272	.234		.282	.251		.172	.168	.195	.162	.106	.124	.202	.180	.123

[1] Most values are standardized [0,1] and mean statistical values lower than .5 are indicated with red color. However, observation values (N) are natural numbers and difference values (Δ_{CK}, Δ_{Enj}, Δ_{Exc}) are normalized [-1,1].
Note: **T**= Treatment (4 is the control treatment); **Stat**= Statistic; **CK**= Total Computational Knowledge Score; **Pre**= Score of Prior (before-treatment) Computational Knowledge; **Post**= Score of Subsequent (after-treatment) Computational Knowledge; $\Delta_{\mathbf{CK}}$= Subsequent minus Prior Computational Knowledge Mean Score (difference); $\mathbf{Enj_1}$= Measurement of Enjoyment before treatment; $\mathbf{Enj_2}$= Measurement of Enjoyment after treatment; $\Delta_{\mathbf{Enj}}$= After-treatment minus Before-treatment Enjoyment (difference); $\mathbf{Exc_1}$= Measurement of Excitement before treatment; $\mathbf{Exc_2}$= Measurement of Excitement after treatment; $\Delta_{\mathbf{Exc}}$= After-treatment minus Before-treatment Excitement (difference); $\mathbf{M_E}$= Index of Motivational Empowerment; $\mathbf{M_U}$= Index of Motivational Usefulness; $\mathbf{M_S}$= Index of Motivational Success; $\mathbf{M_I}$= Index of Motivational Interest; $\mathbf{T_A}$= Personality Index of Agreeableness; $\mathbf{T_C}$= Personality Index of Conscientiousness; $\mathbf{T_E}$= Personality Index of Extraversion; $\mathbf{T_N}$= Personality Index of Neuroticism; $\mathbf{T_O}$= Personality Index of Openess to experience.

Table 12: Research Session - Duration of Survey Parts

T	**Stat**	**Age**	**CK_d**	**Pre_d**	**$Post_d$**	Δ(sec)	Δ%	**P_{Pre}**	**S_d (min)**
1	N	28	30	30	30			30	30
1	MIN	19.0	.151	.195	.107			-.226	27.5
1	MAX	65.0	.697	.715	.680			.253	11.8
1	MEAN	26.4	.389	.432	.345	-128	-20.3	.037	5.6
1	STD	9.2	.155	.154	.155			.130	21.2
2	N	28	30	30	30			30	30
2	MIN	18.0	.137	.171	.104			-.244	24.2
2	MAX	44.0	.769	.757	.782			.300	123.4
2	MEAN	26.2	.396	.435	.357	-113	-17.9	.039	51.0
2	STD	6.1	.151	.147	.155			.125	19.7
3	N	30	30	30	30			30	30
3	MIN	18.0	.175	.187	.163			-.214	28.6
3	MAX	46.0	.669	.657	.681			.277	9.7
3	MEAN	26.1	.329	.367	.290	-113	-21.0	.009	43.3
3	STD	6.6	.105	.108	.101			.125	12.6
4	N	29	30	30	30			30	30
4	MIN	2.0	.138	.114	.162			-.182	27.1
4	MAX	48.0	.752	.805	.698			.299	101.2
4	MEAN	28.9	.394	.427	.361	-97	-15.6	.053	47.1
4	STD	8.6	.145	.168	.123			.125	16.3

Note: **T**= Treatment (1 is Computational Thinking; 2 is Computational Thinking for Sound Production; 3 is Computational Thinking for Multimodal Sound Production; 4 is video watching); **Stat**= Statistic; **CK_d**=Combined Duration of Computational Knowledge (CK) Quizzes 1 & 2; **Pre_d**= Duration of CK Quiz 1, before Treatment; **$Post_d$**= Duration of CK Quiz 2, after Treatment; Δ(sec); Δ%= Difference between Quiz 1 and 2; **P_{Pre}**= Potential for improvement between Quiz 1 and 2; **S_d (min)**= Duration of research session in minutes.

4.1.1 Internal Reliability

The standardized coefficient alpha was estimated for each scale:

1. Computational Knowledge (CK) $\alpha = .77$ - Subscales: Prior Computational Knowledge (CK_Pre) $\alpha = .65$; Subsequent Computational Knowledge (CK_Post) $\alpha = .62$.

2. Core-Affect in time 1 (Enj_1 & Exc_1) $\alpha = .77$.

3. Core-Affect in time 2 (Enj_2 & Exc_2) $\alpha = .86$.

4. Academic Motivation: Empowerment (M_E) $\alpha = .85$; Usefulness (M_U) $\alpha = .96$; Success

(M_S) $\alpha = .93$, and Interest (M_I) $\alpha = .94$.

5. Big-Five Inventory: Agreeableness (P_A) $\alpha = .72$; Conscientiousness (BFI_C) $\alpha = .85$; Extraversion (P_E) $\alpha = .89$; (P_N) Neuroticism α $\alpha = .84$; Openness-to-Experience (P_O) $\alpha = .84$.

4.2 Findings

4.2.1 Hypotheses 1.*

H1.1 The difference in score between Subsequent Computational Knowledge (Mean= .579; SD = .203) and Prior Computational Knowledge (Mean = .540; SD = .222) for Treatment 1 is not significant at the .1 level [$t(29) = 1.16$; $p = .254$].

H1.2 The difference in score between Subsequent Computational Knowledge (Mean= .599; SD = .183) and Prior Computational Knowledge (Mean= .550; SD = .180) for Treatment 2 **is significant** at the .1 level [$t(29) = 1.53$; $p = .069$].

H1.3 The difference in score between Subsequent Computational Knowledge (Mean= .605; SD = .162) and Prior Computational Knowledge (Mean = .603; SD = .187) for Treatment 3 is not significant at the .1 level [$t(29) = .06$].

H1.4 The difference in score between Subsequent Computational Knowledge (Mean= .593; SD = .168) and Prior Computational Knowledge (Mean = .521; SD = .205) for Treatment 4 **is significant** at the .1 level [$t(29) = 2.43$; $p = .022$].

H1.5 In an analysis of covariance (ANCOVA) the Subsequent Computational Knowledge between treatments is not significantly different at the .1 level ($F_{3,116} = .14$, $p = .938$).

4.2.2 Hypotheses 2.*

H2.1 For Treatment 1 (visual programming), the difference between Enjoyment in time 2 (Mean = .413; SD = .312) and Enjoyment in time 1 (Mean = .383; SD = .300) is not significant at the .1 level [$t(26) = .67$; $p = .511$].

H2.2 For Treatment 1, the difference between Excitement in time 2 (Mean = .371; SD = .316) and Excitement in time 1 (Mean = .435; SD = .322) is not significant at the .1 level [$t(26) = -1.03$; $p = .311$].

H2.3 For Treatment 2 (visual programming for sound production), the difference between Enjoyment in time 2 (Mean = .504; SD = .308) and Enjoyment in time 1 (Mean = .485; SD = .293) is not significant at the .1 level [$t(29) = .41$; $p = .684$].

H2.4 For Treatment 2, the difference between Excitement in time 2 (Mean = .421; SD = .287) and Excitement in time 1 (Mean = .550; SD = .295) **is significant** at the .1 level [$t(29) = -2.69$; $p = .012$].

H2.5 For Treatment 3 (visual programming for sound production including a virtual instrument), the difference between Enjoyment in time 2 (Mean = .369; SD = .305) and Enjoyment in time 1 (Mean = .373; SD = .285) is not significant at the .1 level [$t(29) = -.05$; $p = .959$].

H2.6 For Treatment 3, the difference between Excitement in time 2 (Mean = .331; SD = .304) and Excitement in time 1 (Mean = .408; SD = .311) is not significant at the .1 level [$t(29) = -1.77$; $p = .089$].

H2.7 For Treatment 4 (video watching), the difference between Enjoyment in time 2 (Mean = .558; SD = .234) and Enjoyment in time 1 (Mean = .418; SD = .272) **is significant** at the .1 level [$t(29) = 2.89$; $p = .007$].

H2.8 For Treatment 4, the difference between Excitement in time 2 (Mean = .450; SD = .251) and Excitement in time 1 (Mean = .505; SD = .282) is not significant at the .1 level [$t(29) = -.93$; $p = .3580$].

H2.9 In a repeated-measures analysis of variance (rANOVA), the difference between Enjoyment in time 2 and Enjoyment in time 1 of the control treatment is not significantly different than the same difference in other treatments at the .05 level ($F_{3,116} = 1.84$, $p = .146$).

H2.10 In a repeated-measures analysis of variance (rANOVA), the difference between Excitement in time 2 (Mean = .513; SD = .179) and Enjoyment in time 1 (Mean = .419; SD = .245) is not significantly different than the same difference in other treatments at the .1 level ($F_{3,116} = 1.46$, $p = .229$).

4.2.3 Hypotheses 3.*

H3.1 In an analysis of variance (ANOVA) the Index of Motivational Empowerment between treatments 1,2,3, and 4 is not significantly different at the .1 level ($F_{3,115} = .650$).

H3.2 In an analysis of variance (ANOVA) the Index of Motivational Usefulness between treatments 2 and 3 **is significantly different** at the .1 level ($F_{3,116} = 2.13$, $p = .100$).

H3.3 In an analysis of variance (ANOVA) the motivational factor of Success between treatments 3 and 4 **is significantly different** at the .1 level ($F_{3,116} = 4.03$, $p = .009$).

H3.4 In an analysis of variance (ANOVA) the motivational factor of Interest between treatments 3 and 2, and between treatments 3 and 4 **are significantly different** at the .1 level ($F_{3,116} = 3.06$, $p = .031$).

Figure 10 shows a detailed empirical model of important correlations. In Appendix B (Section 7), Table 47 shows the correlation between important variables from the data analysis.

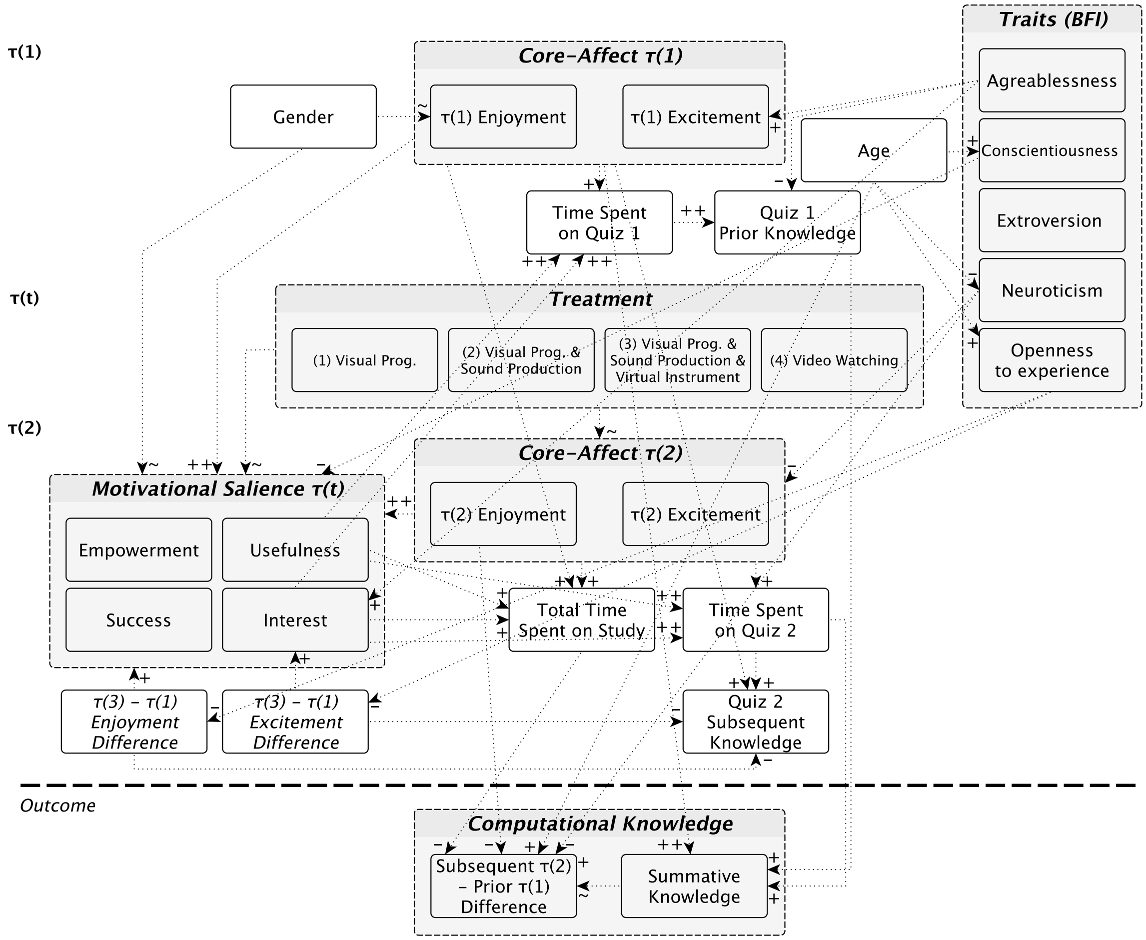


Figure 10: *Empirical Data Model:* Correlations among Variables (see Appendix B, Table 47).

Note: $\tau(1)$ denotes the period of time from the beginning of the study until the treatment; $\tau(t)$ denotes the period of time during the treatment; $\tau(2)$ denotes the period of time from after the treatment until the end of the study; + denotes a positive correlation; - denotes a negative correlation; ~ denotes a variable correlation due to multiple variable levels; A double symbol denotes correlation higher than .25. See Table 47 in Section 7.1 for a complete table of correlations.

4.2.4 *Computational Knowledge*

Computational Knowledge was measured using two sub-scales, one before and one after Treatment.

1. Between treatments, the differences between Prior and Subsequent Computational Knowledge are not significant at the .1 level ($F_{3,112} = .14$, $p = .938$).

2. In Treatment 4 (video watching), the difference between Prior (Mean= .521; SD= .205) and Subsequent (Mean= .593; SD= .168) Computational Knowledge **is significant** at the .1 level [$t(29) = 2.43$; $p = .022$].

3. Between and within treatments, a general linear regression model supports the proposed Affective Model for the Practice of Computational Thinking through Self-Expression. The regression model **is significant** at the .1 level ($F_{16,97} = 3.03$, $p = .001$) and explains 33% of the difference between Prior and Subsequent Computational Knowledge with 5 factor predictors that are all significant at the .1 level.

4. Regardless of treatment, Computational Knowledge is partially explained (14%) by the difference in Enjoyment between Times 1 and 2, and the combined duration of Quizzes 1 and 2 ($F_{2,116} = 9.57$, $p = .0001$). And Subsequent Computational Knowledge is partially explained (35%) by Prior Computational Knowledge ($F_{1,118} = 63.49$, $p < .001$).

4.2.5 *Enjoyment & Excitement*

Core-Affect is a two-dimensional construct consisting of the affective states of Enjoyment and Excitement, which were measured before and after Treatment.

1. Between treatments, there are no significant differences in Enjoyment before treatment at the .1 level ($F_{3,116} = .93$, $p = .430$).

2. Between treatments, there are no significant differences in Excitement before treatment at the .1 level ($F_{3,116} = 1.38$, $p = .255$).

3. Between treatments 3 and 4, there is **a significant difference** in Enjoyment after treatment at the .1 level ($F_{3,116} = 2.57$, $p = .058$).

4. Between treatments, there are no significant differences in Excitement after treatment at the .1 level ($F_{3,116} = .99$, $p = .398$).

5. The difference in Enjoyment before and after treatment **is significant** between Treatment 3 (visual programming for sound production including a virtual instrument) and 4 (video watching) at the .1 level ($F_{3,116} = 1.38$, $p = .255$).

6. In Treatment 2 (visual programming for sound production), the difference in Excitement after and before treatment **is significant** at the .1 level ($t(29) = -2.69$; $p = .012$).

7. Enjoyment after treatment (Mean = .461; SD = .297) correlates highly (.759) with Excitement after treatment (Mean = .393; SD = .290). However, only Enjoyment after treatment **is a significant predictor** at the .1 level in a multiple regression model for Motivation:

   a) Motivational Empowerment (Mean = .600; SD = .193): OLS Type I - $F_{1,115} = 16.82$, $p < .0001$; OLS Type III - $F_{1,115} = 3.41$, $p = .068$.

   b) Motivational Usefulness (Mean = .423; SD = .210): OLS Type I - $F_{1,116} = 66.89$, $p < .0001$; OLS Type III - $F_{1,116} = 10.81$, $p = .001$.

   c) Motivational Success (Mean = .569; SD = .226): OLS Type I - $F_{1,116} = 58.93$, $p < .0001$; OLS Type III - $F_{1,116} = 18.90$, $p < .0001$.

   d) Motivational Interest (Mean = .532; SD = .204): OLS Type I - $F_{1,116} = 193.82$, $p < .0001$; OLS Type III - $F_{1,116} = 33.45$, $p < .0001$.

4.2.6 *Motivational Salience*

Motivational Salience was measured once after Treatment with regard to the learning activity during Treatment.

1. Between treatments, Motivational Empowerment is not significantly different at the .1 level ($F_{3,115} = .65$, $p = .585$).

2. Motivational Usefulness **is significantly different** at the .1 level ($F_{3,116} = 2.13$, $p = .100$) between Treatment 2 (visual programming for sound production) and Treatment 3 (visual programming for heuristic sound production).

3. Motivational Success **is significantly different** at the .1 level ($F_{3,116} = 4.03$, $p = .009$) between Treatment 3 (visual programming for heuristic sound production) and Treatment 4 (video watching).

4. Motivational Interest **is significantly different** at the .1 level ($F_{3,116} = 3.06$, $p = .031$) between Treatment 3 (visual programming for heuristic sound production) and Treatment 2 (visual programming for sound production), and between Treatment 3 and Treatment 4 (video watching).

5. Although Motivational Usefulness ($r = .331$, $p = .0002$), Success ($r = .157$, $p = .088$), and Interest ($r = .273$, $p = .003$) **correlate significantly** and positively with the combined Duration of Quizzes 1 and 2, they do not correlate significantly with Computational Knowledge Scores ($r = -.054$, $p = .56$; $r = .129$, $p = .161$, and $r = -.047$, $p = .607$ respectively).

6. Enjoyment after Treatment explained 18% of Motivational Empowerment in a linear regression model ($F_{4,114} = 6.30$, $p = .0001$).

7. Enjoyment after Treatment, and Excitement before and after Treatment explained 47% of Motivational Usefulness in a linear regression model ($F_{12,107} = 7.86$, $p < .0001$).

8. Enjoyment before and after Treatment, and Treatment explained 55% of Motivational Success ($F_{11,108} = 12.09$, $p < .0001$).

9. Enjoyment before and after Treatment, and Excitement after Treatment explained 72% of Motivational Interest ($F_{12,107} = 22.30$, $p < .0001$).

4.2.7 Demographics

1. Age correlates significantly with BFI's Neuroticism ($r = -.265$; $p = .004$) and Openness-to-experience ($r = .192$; $p = .040$), and also with the difference between Prior and Subsequent Computational Knowledge ($r = .255$; $p = .006$) at the .1 level.

2. The difference between Prior and Subsequent Computational Knowledge correlates significantly with BFI's Neuroticism ($r = -.200$; $p = .029$) at the .1 level.

4.2.8 Subject Pooling

The sample is further analyzed by pooling subjects based on specific characteristics. The relevant tables are shown in Appendix B (Section 7). Table 13 shows the estimated probability of subjects' predefined characteristics across the four treatment groups. Using these probabilities it is possible to estimate how much more or less likely is one characteristic from another. Table 13 shows how the focal variables Computational Knowledge, Enjoyment, and Excitement differ between treatments.

Table 13: Probability Estimation - Predefined Characteristics across Treatment Groups

Characteristics			**Treatment Groups**			
			1	**2**	**3**	**4**
		$\Delta_{\text{CK}} > .083$	.433	.400	.300	.433
		$\Delta_{\text{CK}} < .083$	.300	.233	.367	.200
		$+\Delta_{\text{CK}}$	.600	.600	.500	.633
		$-\Delta_{\text{CK}}$	.400	.400	.500	.333
		$+\Delta_{\text{Enj}}$	.433	.533	.367	.700
		$-\Delta_{\text{Enj}}$	.300	.333	.500	.200
		$+\Delta_{\text{Exc}}$	.333	.267	.333	.433
		$-\Delta_{\text{Exc}}$	.333	.467	.500	.433
	$+\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.100	.167	.067	.300
	$-\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.033	.067	.067	.067
	$+\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.300	.200	.233	.367
	$-\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.233	.267	.400	.133
	$+\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	.200	.367	.133	.433
	$-\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	.133	.133	.233	.067
	$+\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	.167	.200	.267	.133
	$-\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	.233	.167	.233	.233
	$+\Delta_{\text{CK}}$	$-\Delta_{\text{Exc}}$	.133	.333	.333	.233
	$-\Delta_{\text{CK}}$	$+\Delta_{\text{Exc}}$	.133	.133	.267	.133
	$+\Delta_{\text{CK}}$	$+\Delta_{\text{Exc}}$	.200	.133	.067	.300
	$-\Delta_{\text{CK}}$	$-\Delta_{\text{Exc}}$	.200	.133	.167	.167
$+\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.167	.133	.033	.267
$+\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.033	.133	.067	.133
$+\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.033	<.033	<.033	.033
$+\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.100	.200	.267	.100
$-\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.133	.067	.200	.100
$-\Delta_{\text{CK}}$	$+\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.067	.033	<.033	.133
$-\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	$+\Delta_{\text{Exc}}$	.133	.067	.200	.100
$-\Delta_{\text{CK}}$	$-\Delta_{\text{Enj}}$	$-\Delta_{\text{Exc}}$	.133	.067	.133	.033

4.2.9 Feedback Textual Analysis

Study subjects could give feedback about the study by writing their comments before the end of the study session. Text terms were mined [177] from subjects' comments and analyzed for association to predefined dictionaries of sentimental terms. Table 14 shows statistics about subjects' comments including estimations about terms associated with sentiment in a dictionary of negative and positive valence terms [175]. Figure 11 shows word terms that were observed in subjects' comments 4 times or more [178]. Additionally, Figures 12, 13, 14, 15, and 16 show a breakdown of emotional terms found in subjects' comments [176].

Table 14: Sentiment Analysis of Subjects' Comments

Tre	Word Count	Sentiment	Negativity	Positivity
1	702	.038	.030	.068
2	519	.012	.040	.052
3	604	.031	.038	.070
4	343	.015	.044	.058
Sample	2168	.026	.037	.063

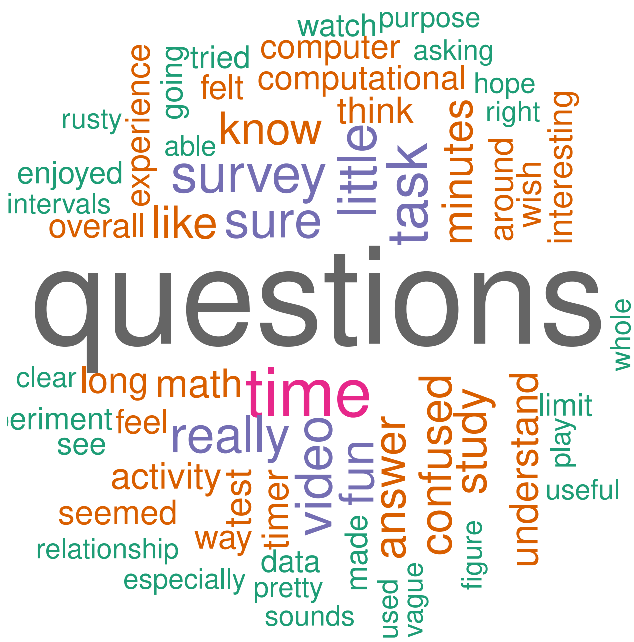


Figure 11: Frequent Terms in Subjects' Comments. Larger letter size means higher number of observations.

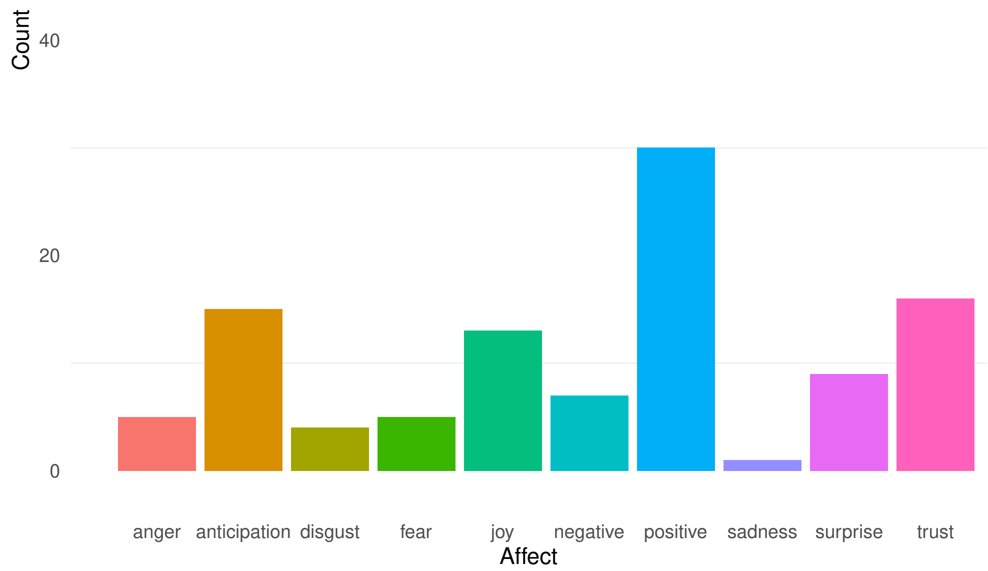


Figure 12: Affect Analysis of Subjects' Textual Comments for Treatment 1, Visual Programming.

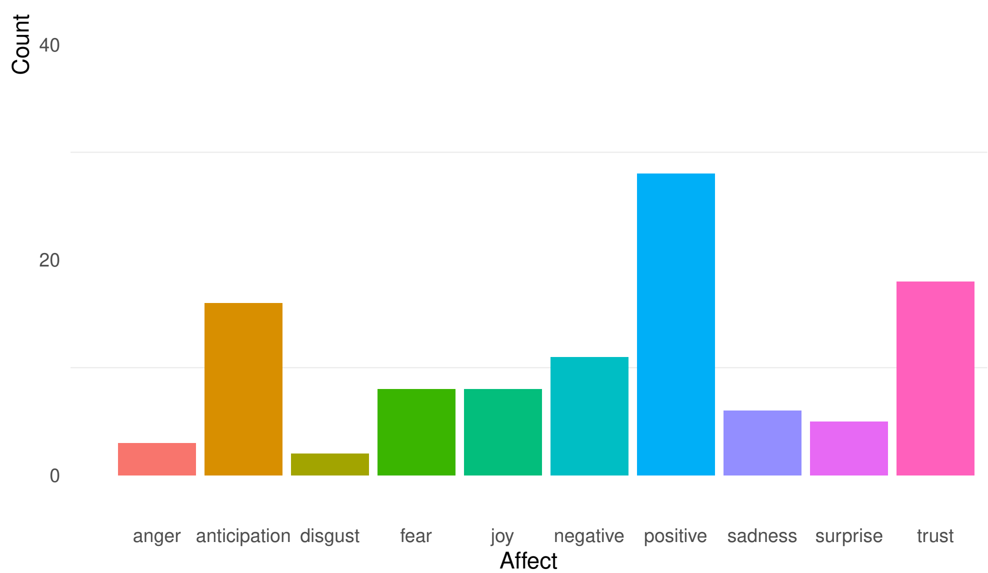


Figure 13: Affect Analysis of Subjects' Textual Comments for Treatment 2, Visual Programming for Sound Production.

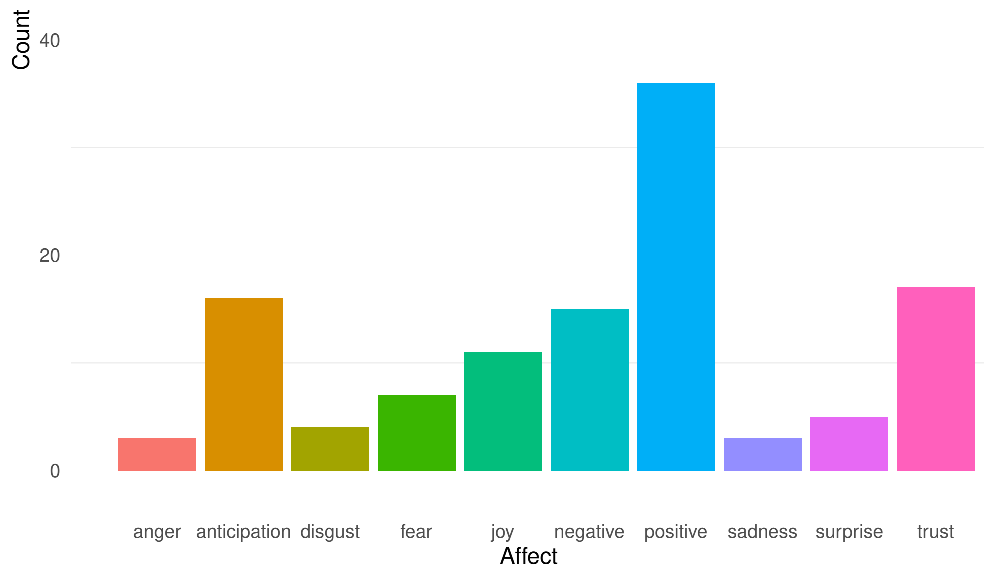


Figure 14: Affect Analysis of Subjects' Textual Comments for Treatment 3, Visual Programming for Sound Production including a Virtual Musical Instrument.

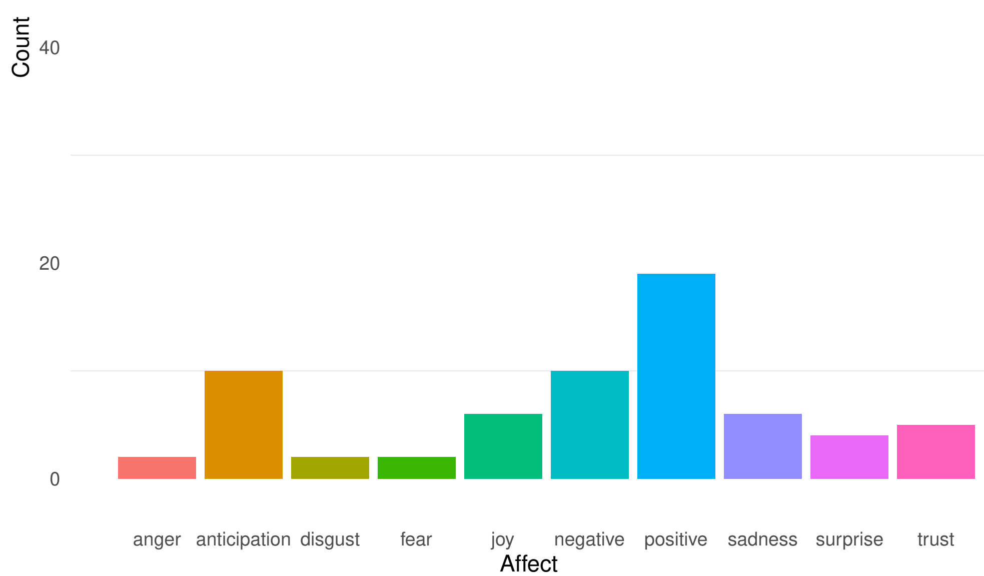


Figure 15: Affect Analysis of Subjects' Textual Comments for Treatment 4, Video Watching of Oceanic Scenery.

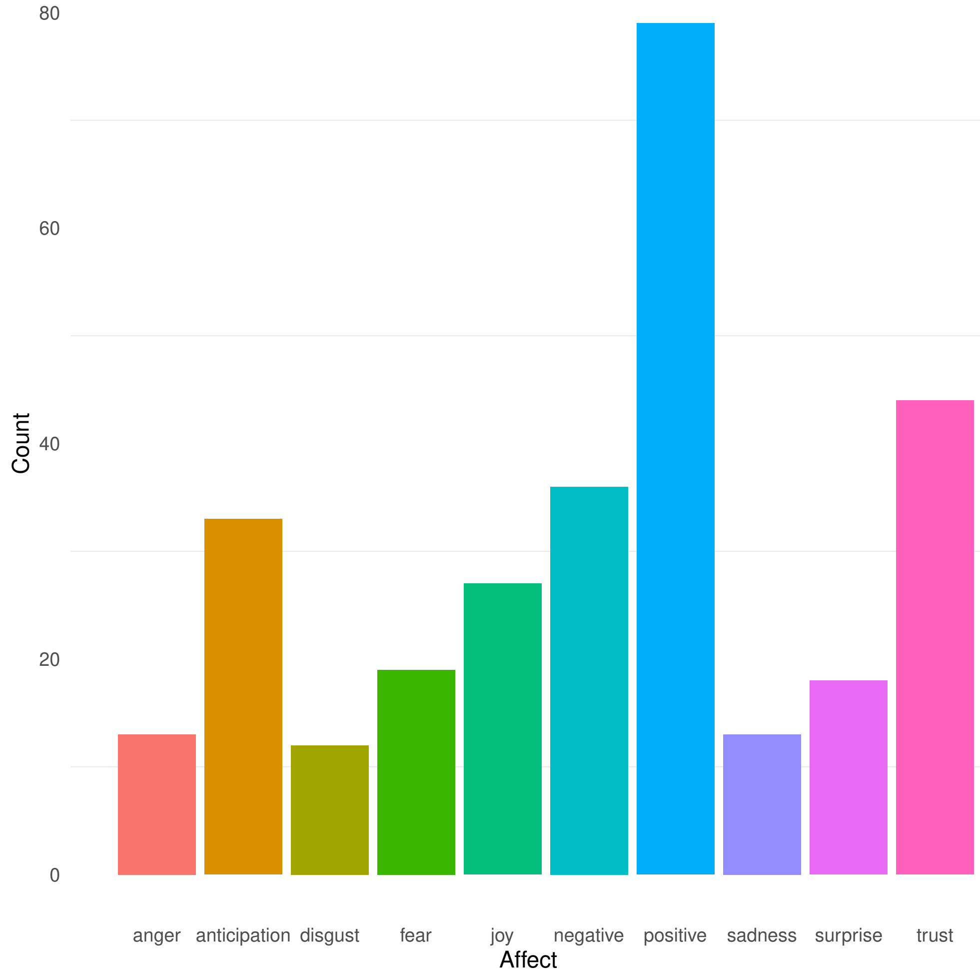


Figure 16: Affect Analysis of Subjects' Textual Comments for whole Sample.

4.3 Summary

The study utilized a pre-test post-test design, which split the sample in four treatment groups. Subjects experienced one of four different Treatments for 10 minutes. Treatment 1 was visual programming; Treatment 2 was visual programming for sound production; Treatment 3 was visual programming for sound production including a virtual instrument, and Treatment 4 was video watching of oceanic scenery. The different treatments correlated significantly with Enjoyment, Excitement, Motivation, and Duration of Quizzes 1 and 2. In more detail, Enjoyment in Time 2 was significantly lower after Treatment 2 than after

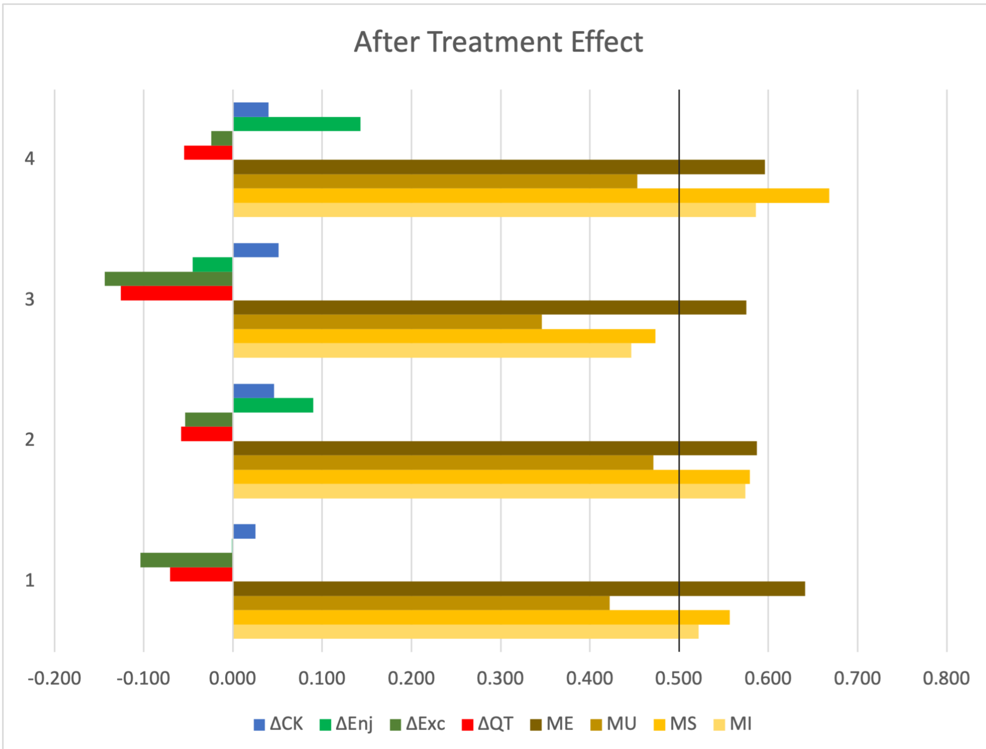
Treatment 4. Excitement in Time 2 (after Treatment) and Motivation were significantly lower after Treatment 3 than after Treatment 2. The combined duration of Quizzes 1 and 2 was significantly lower during Treatment 3 than during all other treatments. On average, lower cognitive effort during a treatment was associated with higher Enjoyment in Time 2 and with a higher difference between Prior and Subsequent Computational Knowledge (as reflected by score differences between Quizzes 1 and 2).

Both Enjoyment and Excitement correlated significantly and positively with Motivation at the .1 level, yet Enjoyment's correlation was higher than Excitement's. Although Enjoyment and Excitement in Time 1 correlated significantly and positively with Prior and Subsequent Computational Knowledge, Excitement was negatively correlated. Enjoyment and Excitement in Time 2 did not significantly correlate with Prior and Subsequent Computational Knowledge. The differences between Enjoyment as well as Excitement in Time 1 and in Time 2 correlated significantly and negatively with Prior and Subsequent Computational Knowledge.

Motivation correlated highly with the combined Duration of Quizzes 1 and 2. The average Duration of Quiz 2 is less than the average Duration of Quiz 1 in all treatment groups. In addition, in all treatment groups the average duration difference between Quizzes 1 and 2 was proportionally smaller to higher reported Motivation.

After Treatment 4 (video watching), Subsequent Computational Knowledge was 7% higher than Prior Computational Knowledge, which was the highest gain among all Treatment groups. The learning activity for each Treatment was 10 minutes, and the Computational Thinking practice (answering Computational Thinking Quiz 1) was on average 9 minutes. Thus, the potential for learning during Quiz 1 and during Treatment was similar. However, the cognitive effort required during each Treatment differed. Hence, the summative learning effect from the combined Computational Thinking practice from Quiz 1 and Treatment was decreased proportionally to the cognitive effort required by the treatment.

Lastly, Figure 17 shows the after treatment effect on the three focal variables (Computational Knowledge; Enjoyment & Excitement, and Motivational Salience) for each of the four treatments, estimated using the average of all treatments for before-treatment measures (Prior Computational Knowledge, Enjoyment, and Excitement).



Note: 1, 2, 3, 4= Treatment 1, 2, 3, and 4 respectively; **ΔCK=** Difference between Prior and Subsequent Computational Knowledge; **ΔEnj=** Difference in Enjoyment between before and after Treatment; **ΔExc=** Difference in Excitement between before and after Treatment; **ΔQT=** Difference in Duration between the before and after Treatment Quizzes; **ME, MU, MS, MI=** After Treatment Motivational Factor of Empowerment, of Usefulness, of Success, and of Interest respectively; Range is [-1,1] except for ME, MU, MS, and MI that have a [0,1] range.

Figure 17: After Treatment Effect on Computational Knowledge and Affective States.

5 Discussion

This study collected empirical evidence that supports the proposed Affective Model for the Practice of Computational Thinking through Self-Expression (see Figure 4 in Section 2.4.1). As discussed previously, learner's affective states during instructional activities are associated to their subjective learning experience [71]. The affective states of Enjoyment, Excitement, and Motivational Interest were significant predictors in a general linear regression model for the difference between Prior and Subsequent Computational Knowledge.

The pre-test post-test study design increased the duration of the research session and the cognitive effort needed before and after the treatment. Higher Enjoyment and Excitement at both Time 1 and Time 2 were associated with longer Study Duration and Duration of Quizzes 1 and 2. Subjects with longer Duration of Quizzes 1 and 2 also on average scored higher in Prior and Subsequent Computational Knowledge. However, higher Enjoyment and Excitement in Time 2, rather than in Time 1, was associated with a lower difference between Prior and Subsequent Computational Knowledge. Video watching (Treatment 4), the least cognitively effortful learning modality, yielded the highest difference between Prior and Subsequent Computational Knowledge and the lowest Prior Computational Knowledge than all other treatments. Visual programming for sound production including a virtual instrument (Treatment 3), the most cognitively effortful learning modality, yielded the lowest difference between Prior and Subsequent Computational Knowledge, but also both the highest Prior and Subsequent Computational Knowledge than all other treatments.

The difference between Prior and Subsequent Computational Knowledge was partially explained (33%) by the subjects' combination of Age and Gender, Core-Affect after treatment, and Motivational Interest after Treatment. The multiple linear regression was performed in accordance with the proposed *Affective Model for the Practice of Computational Thinking through Self-Expression* (see Figure 4), and the proposed model predictors were significant predictors in the regression analysis.

The affective states in the Pleasure-Arousal theory [67] explained motivational factors in the academic motivation theory [73]. This means learners' feelings of enjoyment and excitement during instructional activities had an effect on their motivation. Notably, enjoyment during instructional activities, correlated more than excitement did with academic motivational factors, which suggests that maintaining enjoyment during instructional activities is a more direct path to academic motivation than excitement is.

Sound Production was successfully integrated into a mode of visual programming. The potential modality effect that sound has on learning through visual programming is to add audible outputs to computations. For example, during learning how to program with virtual objects as computational abstractions, learners make sense of visual scaffolding to reason with and develop computations [6, 172]. However, the meaning of the sound and of the programming are different. Sound can be an auditory display that confirms effective programming or indicates programming faults by its pitch, texture (timbre), or absence.

Treatment 2 integrated sound production and visual programming within a learning multimodality and yielded greater learning than did Treatment 1, which was visual programming alone. However, sound production should be integrated with visual programming within a multimode of learning by a single, cohesive user input/output interface, and not by a combination of two virtual user input/output interfaces, because additional interfaces required increased cognitive effort.

High cognitive effort is intrinsic to the practice of computational thinking, and the intersemiotic relationships among learning modalities play a critical role in cognitive loads during practice [103]. The use of learning manipulatives can make instructional activities more desirable to learners. However, when manipulatives are not perceived as part of a coherent instructional activity, then manipulatives could derail the learning process [63]. Moreover, although physical manipulatives offer concrete experiences, virtual manipulatives can more easily change form and functionality to support different levels of thinking and knowledge.

In the context of instructional systems design, multimodality is a key principle [104], because it directly affects learners' enjoyment and excitement.

The practice of computational thinking is a matter reasoning. Thus it requires cognitive effort [79]. As suggested from the empirical data of this study, learners start practicing motivated by their excitement, however as time goes by their motivation depends more on their enjoyment during practice.

In the context of computational thinking practice, manipulatives can offer programmable features. Moyer-Packenham and Bolyard define and discuss the virtual manipulative as "an interactive, technology-enabled visual representation of a dynamic mathematical object, including all of the programmable features that allow it to be manipulated, that presents opportunities for constructing mathematical knowledge" [180, p. 3]. The data presented in this dissertation suggest that computational knowledge can be constructed in a similar approach involving virtual objects with dynamic states that offer programmable features to practice algorithm design.

Manipulatives can enable instructional assessments based on practice rather than theoretical writings that are usually compared against textbook content. Additionally, manipulatives could exploit users' anchoring heuristic [181]. By providing insightful code for programmable manipulatives, users' self-efficacy can be increased due to their successful use of the manipulatives [182].

Manipulatives can support instruction by assigning meaning to the outputs of learning activities. As a manipulative, a musical instrument enables self-expression through musical expression. Learning activities with sound production as their output would benefit from using musical instruments as manipulatives. However, manipulatives increase cognitive effort during learning activities.

Cognitive effort may distract learners from performing the learning activity, and decrease learners' enjoyment which drives motivation. However, multitiered learning activities could offer a different manipulative variation for each tier that aims to be less difficult to use. While modular physical manipulatives may allow for a certain number of variations, substituting one variation with another among instructional activities is easier with virtual manipulatives.

This dissertation applied visual and musical modalities. A blend of two distinct learning modalities forms a multimodality. The complexity of multimodality must be observed through the lenses of subjective experience [183], meaning that people could perceive the same phenomenon in different ways. The concept of multimodality is helpful in analyzing complex artifacts that blend different semiotic resources with which learners reason.

As a learning modality, visual programming offers visuals that clarify programming structures. While a few visuals may help learners focus on designing programming structures, as their number grows, they require a higher cognitive effort to be processed. The same effect occurs when the informational complexity of visuals increases. Therefore, the inclusion of cognitive breaks during instructional activities is critical for learners' motivation, due to the effects that cognitive fatigue has on memory and attention [167].

Theory on learning modalities and styles suggests that learners may learn more through one learning modality and less through another [54]. Self-efficacy during instructional activities plays an important role in academic motivation [47], however it is not sufficient. Learners' enjoyment and excitement are also important for increasing and sustaining academic motivation.

A blend of visual and auditory modalities may be cohesive but not coherent. For visual and auditory modalities to be coherent, the visuals must correspond to the produced sound. Thresholds of correspondence between visuals and audio are subject to learners' subjective experience. For example, a physical musical instrument may have more or less obscure controls that correspond to the produced sound. Keyboard and strings are visually and aurally more coherent than valves and buttons in wind instruments, because wind instruments depend also on the air pressure to produce sound and pitch.

When the modality of the learning activity required more cognitive effort, then the subjects' focal affective states (Enjoyment, Excitement and Motivation) decreased. Treatments 1, 2, and 3 were learning activities with modalities that progressively required more effort and resulted in progressively stronger cognitive fatigue, which decreased subjects' focal affective states. Thus, the summative learning effect from practicing computational thinking during Quiz 1 and from each treatment's learning activity was reduced proportionally to the cognitive fatigue associated with the treatment.

The empirical data of this study suggest that the enjoyment of an instructional activity correlates with the learners' feeling of empowerment, and the feeling of being successful during the instructional activity. Both the usefulness of an instructional activity and learners' feeling of being interested correlate with both their feelings of enjoyment and excitement. Based on these correlations, instructional design should aim to produce learning activities that are multimodal and have multitiered goals starting from easy, for the intended learners, activities. This approach enables learners to choose their preferred learning modalities and also feel more successful by achieving goals in learning tiers that match their levels of thinking and knowledge.

Standardizing methods for computational thinking practice will enable teachers to share resources, and could lead to the development of vocational training in designing formal curricula. Researchers would also benefit from comparable measures across studies that will facilitate meta-analyses. The development of formal curricula for the practice of computational thinking will be limited for as long as methods for the assessment of such instructional activities are not broadly accepted and utilized.

This study had some limitations: The treatment was a single, 10 minute intervention, which limited the effectiveness of the treatment. Moreover, the study was based on a single educational subject and may not be generalizable to other educational topics. The data utilized were self-reported, and future studies could use autonomic or neurological indicators of enjoyment and excitement to more accurately and biologically measure these variables. Also, because participants took the study online, there is no data on how attentive participants were during the treatment. However, in online and self-regulated learning it is realistic not to know how attentive a learner is during instructional activities.

Conducting this study online had some implications on data collection and the recruitment of participants. The online invitation for the study received a high number of automated and duplicate responses from potential participants, which were suspected to be bots and some individuals repeating the survey to receive additional compensation. For example, multiple different email addresses were used from the same IP address and some responses provided duplicate, repetitive, and out-of-range answers to the online survey. Such data required additional data cleaning and exclusion of some participants. However, taking this study online made it possible to reach a broader audience of participants outside of Virginia Tech, expanding the age group and diversifying the sample population. This means that the findings of the study could be more generalizable than if this study was performed in a physical location and consequently restricted to undergraduate participants.

Lastly, the analysis of visual and auditory semiotics is important because it can describe learners' interaction with visual and auditory learning modalities. Sound is a powerful semiotic resource that can turn a cognitively effortful practice into a more enjoyable activity of musical expression.

5.1 Future Research

Future research is needed to compare two treatment groups that will practice the same instructional activity, with one using the physical musical instrument and the other the virtual musical instrument. Additionally, a longitudinal study is needed to investigate the correlation between learners' focal affective states (Enjoyment, Excitement, Motivation), and their gain and retention of computational knowledge during a period of self-regulated practice, and a large number of available instructional activities to choose from.

Future work could also focus on creating an online collaborative platform, where learners can work jointly on the same instructional activity via their internet browsers. This opportunity for collaborative work would more accurately mimic the classroom instructional environment in which students and teachers frequently interact. It would also allow for both peer-to-peer engagement and teacher-to-student education and lesson individualization to occur without the time, resource, and knowledge intensive need to acquire and setup equipment. The current data communication between learning resources over an encrypted WebSocket connection allows for synchronous instructional activities with multiple participants.

5.2 Conclusions

This dissertation investigated learning modalities for self-expression through visual and musical computing. New theoretical developments presented in this dissertation are:

1. A literature review on the construct of computational thinking;
2. A novel nomological network for the construct of computational thinking;
3. An affective instructional model based on self-expression through computing. The model was supported by empirical data collected through a study of visual and musical modalities for the practice of computational thinking; as well as through prior work [8].
4. A novel approach to the assessment of instructional activities for cognitive practice, and
5. An instructional apparatus for musical computing including physical and virtual manipulatives.

Instructional activities for cognitive practice should intentionally periodically interrupt the cognitive effort, in order to allow learners to have cognitive breaks. Distributing cognitive effort within periods of higher motivation, may result in increased learners' enjoyment of instructional activities.

This study exemplified the use of musical computing for the practice of computational thinking. Musical computing can be a way of practicing computational thinking that learners may find enjoyable and engaging.

6 Appendix A

6.1 Long Textual Tables of Literature Review

Computational Thinking Perspective *Common Characteristic*	**Source**
Cognitive Process *a.* -“Think in abstractions” -“Think in terms of decomposition” -“Think algorithmically” -“Think in terms of evaluations” -“Think in generalizations”	*a.* [184]
b. -“Computational concepts” -“Computational practices” -“Computational perspectives”	*b.* [185]
c. - Computational thinking “is the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent.”	*c.* [10]
“Complex Systems Thinking” -“Seeing computation across domains that are not necessarily computer scientific.”	[186]
Skill Set *a.* -“Decomposition, Pattern Recognition, Abstractions, Algorithms.”	*a.* [44]
b. -“Abstraction, Algorithmic thinking, Problem-solving, Decomposition, Generalization, and Debugging.”	*b.* [39]
c. “Decomposition, Pattern generalization and abstraction, Pattern recognition, Algorithm design, Data analysis and visualization.”	*c.* [45]
Subset of the “scientific method” -“Problem Formulation (Abstraction)” -“Solution Expression (Automation)” -“Execution & Evaluation (Analysis)”	[187]
Capabilities & Competencies	

a. -"Data collection, Data analysis, Data representation, Problem Decomposition, Abstraction, Algorithms & procedures, Automation, Parallelization, Simulation." *b.* -"Abstraction, Decomposition, Patterns (Recognition and Generalization), Algorithms, Data (Collection, Analysis, and Representation), Parallelism, Iteration, Simulation (and Automation), Testing and Debugging."	*a.* [46] *b.* [43]
"Horn-Carroll (CHC) model of intelligence" -"Fluid reasoning, Visual processing, Short-term memory."	[115]
"Components of Computational Thinking" in the "Ideation Process" -"Identify the problem - Decomposition" -"Research the problem - Pattern Recognition" -"Find Solutions - Abstraction" -"Choose the best possible solution - Algorithm"	[42]
Conceptual Framework -"Computational Thinking is a conceptual framework that enables programming." -"Someone schooled in the principles of Computational Thinking can find computational solutions to problems in any domain."	[188]
"Digital Competence" -"Problem solving (22%)" -"Abstraction (13%)" -"Computer (13%)" -"Process (9%)" -"Science (7%)" -"Data (7%)" -"Effective (6%)" -"Algorithm (6%)" - "Concepts (5%)" -"Ability (5%)" -"Tools (4%)" - "Analysing (4%)"	[40]
"Electronic Computational Thinking" & "Biological Computational Thinking" -"Thinking generated and facilitated by computation, regardless of the device that does the computation"	[189]
Kindergarten through 12^{th} *grade (K-12) Education*	

-“Formulating problems in a way that enables us to use a computer and other tools to help solve them. Logically organizing and analyzing data. Representing data through abstractions such as models and simulations. Automating solutions through algorithmic thinking (a series of ordered steps). Identifying, analyzing, and implementing possible solutions with the goal of achieving the most efficient and effective combination of steps and resources. Generalizing and transferring this problem solving process to a wide variety of problems.”	[190]
“Creative programming” *“Analysis:”* 1. “Problem identification” 2. “Organize and model the situation” *“Technological literacy:”* 3. “Code literacy (algorithms, logic...)” 4. “Technological systems literacy” *“Making/digital creation:”* 5. “Create a computer program” 6. “Evaluation and iterative improvement”	[41]
“Problem solving” *“Problem solving”:* -“Problem formulation” -“Problem decomposition” -“Representation of states” *“Toward automation”:* -“Data structures” -“Flows of controls” -“Recursive procedures” *“Innovative applications”:* -“Computational Thinking is for everyone” -“Computational Thinking is everywhere”	[38]
Definition -“The conceptual foundation required to solve problems effectively and efficiently (i.e., algorithmically, with or without the assistance of computers) with solutions that are reusable in different contexts.”	[157]

Table 15: Definitions and Perspectives of Computational Thinking.

Computational Thinking Modules and Activities *Context (sample)*	**Source**
MOOC (K-6)	

-“Introduction” -“Data - Patterns & Play” -“Data - Representation” -“Digital Systems” -“Information Systems” -“Algorithms & Programming” -“Visual Programming”	[20]
“Digital game-play” (unreported) -“Problem identification and decomposition” -“Creating efficient and repeatable patterns” -“Practicing debug-mode” -“Brainstorming”	[21]
“Robot design” (middle school) -“Algorithmic thinking” -“Patterns” -“Debugging” -“Abstraction” -“Decomposition and iterative design”	[22]
Computational Thinking curricula (middle school) -“Abstractions and pattern generalizations (including models and simulations)” -“Systematic processing of information” -“Symbol systems and representations” -“Algorithmic notions of flow of control” -“Structured problem decomposition (modularizing)” -“Iterative, recursive, and parallel thinking” -“Conditional logic” -“Efficiency and performance constraints” -“Debugging and systematic error detection”	[23]
Knowledge construction (college) -“Organization: Coding style, Data organization” -“Construction: Following procedures, Visualizing data” -“Analysis: Interpretation, Conclusions”	[24]
Visual paired programming (K-12) -“Sequence” -“Iteration (loop and nest loop)” -“Conditional statements” -“User interface design”	[25]
Programming (unreported)	

-"Specifically define the learning and teaching objectives" -"Include appropriate educational tools and strategies such as the design and use of concept maps" -"Consider and understand the differences between novices and experts in programming"	[191]
"Classroom talk" (11-13 years of age) -Programming of a poem with fixed structure, but variable output	[26]
"Computer science course" (college) -"Introduction to Computer (Hardware, Software)" -"Understanding Number System -"Introduction to Operating System" -"Introduction to Disk Operating System (DOS)" -"Application Software" -"Office Suit – word, excel" -"Office Suit – ppt slide, access" -"Networking Basic" -"Website building - HTML I" -"Website building - HTML II" -"Programming Logic I – flowchart, variable, sequence structure" -"Programming Logic II – selection, loop structure, structured logic" -"Visual Programming – Scratch I" -"Visual Programming – Scratch II" -"Robot and programming"	[27]
Course"based on metaphors" (9–12 years of age) -"Program, sequence, memory and variable" -"Input and Output" -"Conditional" -"Loop"	[28]
Formal college course (college) -"To impart the ability to approach problem solving in a systematic and logical manner" -"To develop the skills to formulate solutions by logically deriving unambiguous step-by-step instructions" -"To enable the skills to apply modular approach both in formulating and realizing the solutions"	[192]
Formal college course (college)	

-“Tinkering” -“Exploration” -“Creative designs” -“Trials and errors” -“Tracing” -“Debugging -“Simulation -“Perseverance” -“Teamwork -“Collaboration” -“Communication”	[38]
FOSS (“early childhood”)	
-“Algorithm” -“Modularity” -“Control Structures” -“Representation” -“Hardware/Software” -“Design process” -“Debugging”	[29]
Programming with or without “manipulatives” (“young learners”)	
-“Sequence” -“Loops” -“Parallelism” -“Events” -“Conditionals” -“Operators” -“Data”	[30]
Teachers (faculty)	
-“Computational and non-computational problems resolution” -“Computational Thinking Pillars: decomposition, pattern recognition, abstraction and algorithm” “Problem-solving” -“Strategies” -“Control Structures: Sequential, Repetitions (simple and conditional), Conditional” -“Variables: Parameterized Programming”	[31]
Robotics (unreported)	

-“Create a new program to turn LEDs on and off” -“Create custom blocks that use a loop to gradually fade an LED and to change colors of a tri-color LED; move servos and motors; use loops to blink lights and move servos between two positions; use nested loops to create complex combinations of lights and motion” -“Write conditionals to control a robot using sensors; use sensor inputs to control the output of motors” -“Create a block to find and return the threshold for a sensor; use sensors in compound Boolean statements” -“Abstraction, reducing complexity, increasing efficiency” -“Use lists to store sensor data” -“List matrices used to record ordered pairs to represent sensor measurements at various times” -“Use the map function to scale data before graphing. Use combine to find the mean of data” -“Acting on input data algorithmically. Controlling multiple outputs”	[32]
“Professional learning communities” (professional teachers) -“Tension between Tool and Learning” -“Tension between Direction and Discovery” -“Tension between Individual and Group” -“Tension between Expert and Novice” -“Tension between Actual and Aspirational” -“Tension between Anthropology and Assessment”	[33]
“Tutorial-Based Learning” (elementary school) -“Introduction to computational thinking and algorithms” -“Introduction to programming concepts (such as succession, variables and expressions)” -“String operations” -“Conditional statements” -“Repetition” -“Procedures and functions” -“Lists (voluntary tutorial)”	[34]
“Low Cost Entry to Computational Thinking” (“youth”) -“Conditional Logic” -“Advanced Conditional Logic” -“Parallelism”	[35]
Classroom (K-12) -“Iterated function system fractals”	[36]
Case Studies (unreported)	

-"Introduction of background material required by the student to understand the statement of the problem and its solution" -"Clear statement of the problem" -"A sample of the program/user dialog to provide the student with test data" -"A collection of computational/critical thinking questions which are keyed to the program listing" -"The program listing with code segments strategically elided which become the student's responsibility (aka, 'missing code')"	[37]

Table 16: Computational Thinking Modules in Curricula for all Education Levels.

Components *Name (for ages)*	**Source**
"T-Maze" (5–9) -"Sensors, wooden blocks, camera, and software" -"Maze escape and maze creation"	[37]
"Game Jam" (11–18) -"Using sensors" -"Implementing at least two levels" -"Checking the learning content, e.g., through a quiz" -"Integration of collision detection" -"Using a foreign language"	[143]
"TAPAS" (college) -"Interaction capabilities; that is, buttons, multi-touch events, mid-air gestures" -"Display capabilities; that is, LEDs, screens" -"Retrieval capabilities; that is, access to storage, user's details (such as his/her Facebook account)" -"Affordance capabilities; that is, shape, haptic"	[193]
"Dr. Scratch" (college) -Programming environment to assess: "abstraction, logic, and flow control."	[41]
"ScratchJr & Lightbot" (6-7) -Program "short stories and games" -"Arrange a fixed set of block-based instructions in a finite program space that tell a robot what to do"	[113]
"Scratch" (10-11) -"English dialogue learning through graphical programming language"	[194]
Case studies ("15-16")	

-“LOGO NXT robot” -“Ultrasonic sensor” -“Tutorials, guides, quizzes” -“Robot control program” -“Modeling” movement	[195]
“WeDo 2.0” (“1-6”) -Guided activities: “Pulling; Speed; Robust Structures; Frog’s Metamorphosis; Plants and Pollinators; Prevent Flooding; Drop and Rescue; Sort to Recycle.”	[196]
“Cinco Adventure Game Tool” (college) -“Control Flow Modelling” -“Game States: Screens and Situations” -“Branches: Sequential Composition and Conditions” -“The Inventory: Stateful Behaviour, Variables, Memory, History” -“Hierarchical Modelling: Abstraction, Refinement, Calls and Recursion” -“Code Generation”	[197]
“MaLT” (“13–15”) -“Graphical & Coding patterns between 3D objects” -“Break down complex 3D structures” -“Animated models, Logo parametric (sub)procedures” -“Variable as parameter, repetition, procedural programming, debugging”	[198]
“Visual programming activities” (college) *Computational Thinking practice:* -“Sequence” -“Selection” -“Simple iteration” -“Nested iteration” -“Testing” *Computational Thinking skills:* -“Abstraction” -“Automation” -“Evaluation”	[199]
“Thinker” (college) -“Physical computing tool kit” based on arduino uno board -“Small project ideas, physically interfacing the various sensor and IO modules, progamming the ideas and debugging them”	[64]
“BRICKO” (“1st – 3rd grade”) -Two-cycle robot with “command bricks” and “floor mats” -Challenge-based playing	[200]
“CodeMapper” (college)	

-"Block-based programming environment" -"Directed acyclic graphs" -"Online code harvesting"	[142]
"Snap" ("K-12") -"Immediate output" -"Text commands are represented as blocks" -"Error prevention"	[36]

Table 17: Educational Tools for the Development of Computational Thinking Skills.

6.2 Protocol Details

Affect Survey 1

The affect survey uses the affective slider to measure *Core-Affect* with a continuous interval, described by Betella and Verschure in "the Affective Slider: A Digital Self-Assessment Scale for the Measurement of Human Emotions" [69]. The following two sliders are presented in random sequence to study participants to ask them to rate how they feel.

- Move the slider to rate your level of Enjoyment:

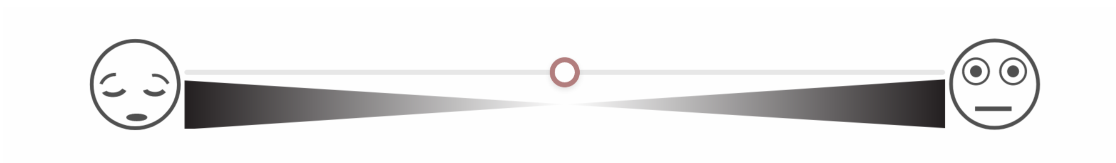


Figure 18: *Affective Slider:* Self-Assessment of Affective Arousal (certain graphics used with creative commons license from [173]).

- Move the slider to rate your level of Excitement:

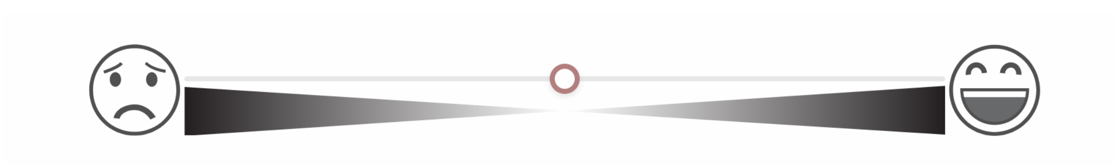


Figure 19: *Affective Slider:* Self-Assessment of Affective Pleasure (certain graphics used with creative commons license from [173]).

Demographics Survey

- Age in years

- Gender; choose from set:

{Female, Male, Non Binary}

- Mood; all that applies from set:

{"alert," "excited," "elated," "happy," "contended," "serene," "relaxed," "calm," "bored," "depressed," "sad," "upset," "stressed," "nervous," "tense"} as specified by Posner et al. in "the circumplex model of affect" [201]

- Hours of sleep the day before

- Big-five Personality Traits Survey as specified by John and Srivastava in "BIG FIVE INVENTORY (BFI)" [202, 203, 204, 205]

Software-Familiarization Instructional Video

Please watch a video that explains the basics of the visual-programming environment "pd-l2ork". Transcript:

'Building & playing modes

- Toggle between building and playing modes to build programs and change computational parameters.

- Click on an icon to put the abstraction on the canvas.

Control & sound abstraction tabs

- Toggle between control and sound abstractions by selecting the control or the sound tab.

Data flow between abstractions

- Virtual wires are used to connect an outlet to an inlet. Inlets are located on the top of abstractions and outlets at the bottom.

- Hover over an outlet to get the cursor to change into a rectangle, then click and drag to connect the outlet to an inlet with a wire. Hold down the shift key while dragging to keep connecting the same outlet to multiple inlets.

Store & recall values within abstractions

- Use the preset abstraction to store and then recall numerical values and choices within abstractions.

- There are four presets. Use the red number-boxes to store a preset and the green number-boxes to recall the corresponding preset.

Sound processing abstractions

- Sound processing abstractions can have both black and cyan inlets and outlets. Cyan outlets and inlets connect via a thicker cyan virtual wire that indicates that sound data flow through them. A black outlet may connect to a cyan inlet.

- Use the speaker abstraction to listen to the sound outcome.

Sensing and controlling

- Use the analog or digital inputs to read analog or binary sensors on a raspberry pi computer platform.

- Channel 6 reads a Photoresistor that varies with light brightness. Use the comment abstraction to document the canvas with useful comments about the program.

Time driven events

- You can time events using the metronome abstraction and count events with the counter.

A help-file per abstraction

- There is a help file per each abstraction that documents its functionality.

- Right-click on any abstraction and choose help to see the help file about that abstraction.

Thank you for watching.'

Affect Survey 2

As described in Section 6.2.

Before-Treatment Questions

As described in Section 6.2.1.

Affect Survey 3

As described in Section 6.2.

Treatment Groups

Figures 20, 21, and 22 show the visual-programming environments for treatment groups A, B, and C respectively. The control-group treatment is a task unrelated to computing: the watching an oceanographic video (no narration or captions). The duration of treatment is the same across all groups (10 minutes).

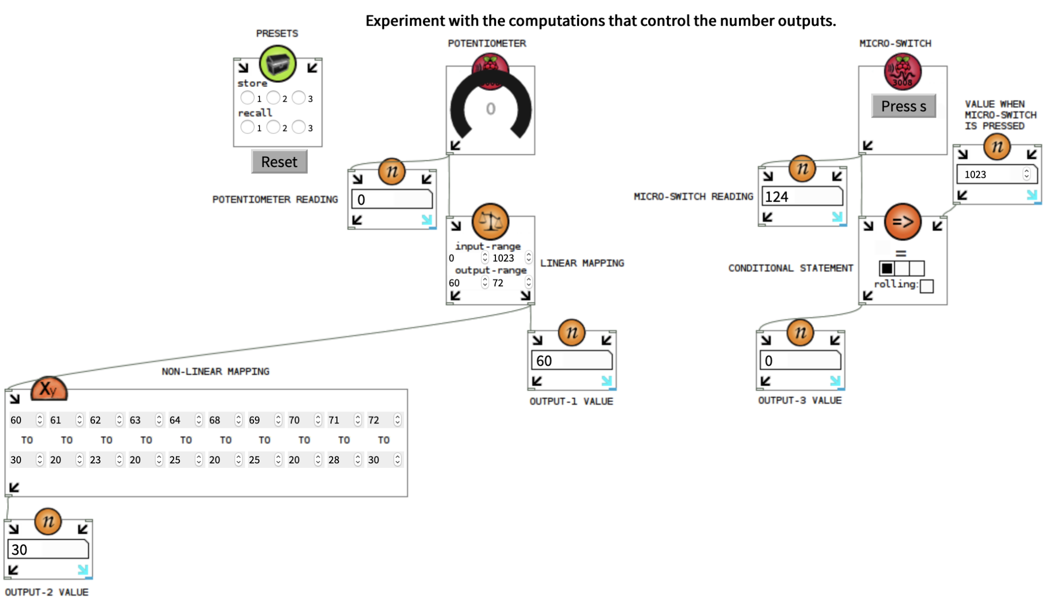


Figure 20: Treatment 1; Visual-Programming.

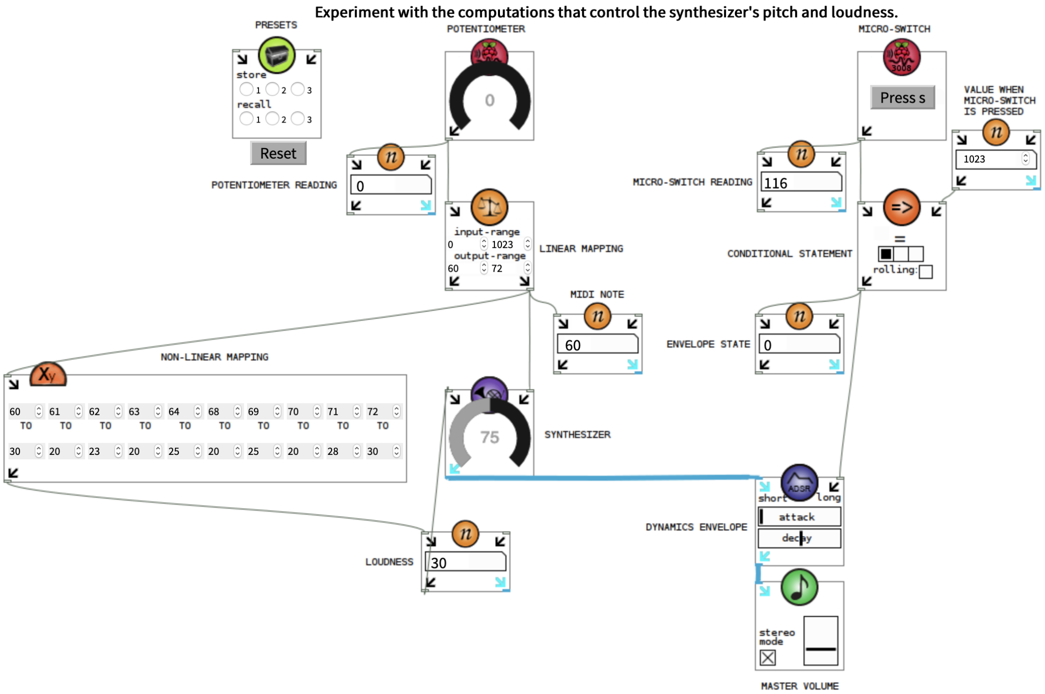


Figure 21: Treatment 2; Visual-Programming for Sound Production.

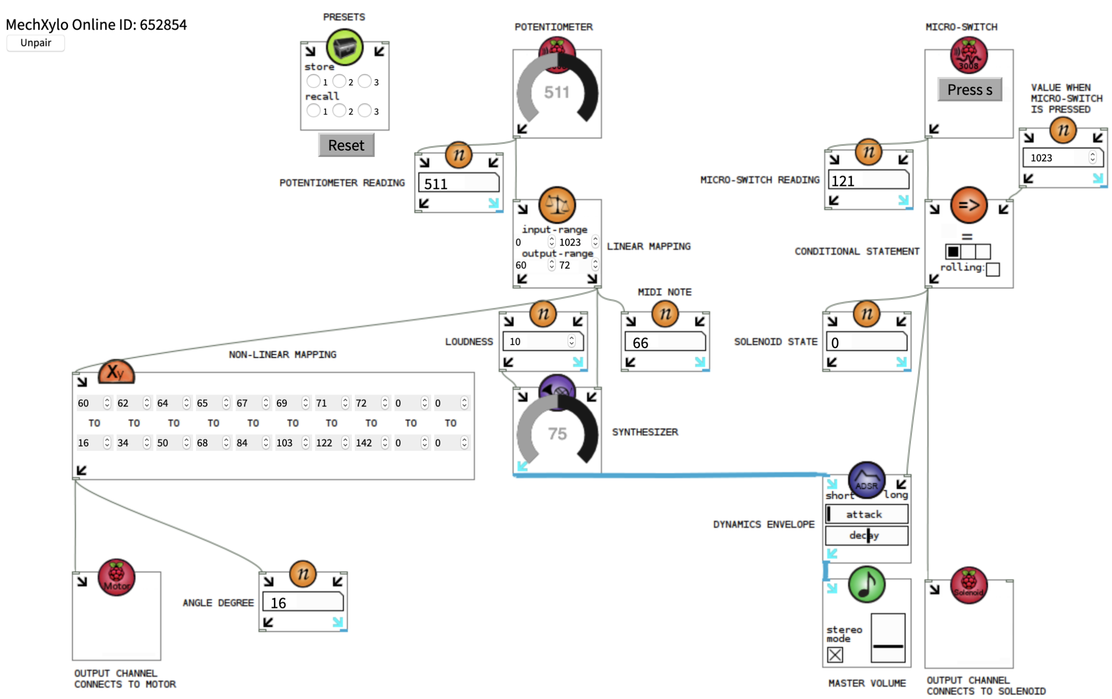


Figure 22: Treatment 3; Visual-Programming for Sound Production including a Virtual Musical Instrument.

Affect Survey 4

As described in Section 6.2.

After-Treatment Questions

As described in Section 6.2.2.

Motivational Factors Survey

Adopted by the inventory as described by Jones in the “User Guide for Assessing the Components of the MUSIC® Model of Motivation” [174].

- The task held my attention.
- I had the opportunity to decide for myself how to meet the task goals.
- In general, the task was useful to me.
- The task was beneficial to me.
- The instructional methods used in this task held my attention.
- I was confident that I could succeed in the task.
- I had the freedom to complete the task my own way.
- I enjoyed the instructional methods used in this task.
- I felt that I could be successful in meeting the academic challenges in this task.
- The instructional methods engaged me in the task.
- I had options in how to achieve the goals of the task.
- I enjoyed completing the task.
- The task was interesting to me.

- Throughout the task, I felt that I could be successful on the task.
- I found the task to be relevant to my future.
- I will be able to use the knowledge I gained in the task.
- The knowledge I gained in this task is important for my future.
- I had flexibility in what I was allowed to do in the task.

Affect Survey 5

As described in Section 6.2.

Reflection Survey

Please ask any questions, and share any comments, thoughts, suggestions, and criticism that you may have. You may do so verbally or in writing.

Affect Survey 6

As described in Section 6.2.

6.2.1 Quiz of Prior Computational Knowledge

1. A scale consists of a range of natural (for example 1, 2, 3) numbers from 100 to 300.
   What are the minimum and maximum limits of the scale's range?
   Rubric challenge $a_{1,1}$ base answer: minimum is 100, maximum is 300.
2. An imaginary phenomenon is measured in imaginary Pha units from 10 to 100.
   What are the necessary minimum and maximum limits of the Pha scale? What is the necessary interval value of the Pha scale?
   Rubric challenge $a_{1,3}$ base answer: minimum 10, maximum 100, interval 1.

3. A phenomenon is measured by an interval scale that consists of a range of natural (for example 1, 2, 3) numbers from 100 to 500.

   Does a measurement of 200 mean that the phenomenon is 2 times stronger than when the measurement is 100?

   Rubric challenge $a_{2,2}$ base answer: No, because the definition of an interval scale does not allow ratios or arbitrary units.

4. A motor can turn from 0 to 180 angle degrees and the smallest turn it can perform is .1 angle degree. A scale consists of the incremental numbers 1, 1.1, 1.2, and so forth up to 180. *Is this scale sufficient to drive the motor to all possible angle positions?*

   Rubric challenge $a_{2,4}$ base answer: No, because it consist of less than 181 units.

5. A questionnaire measures customer satisfaction as: very satisfied, satisfied, unsatisfied, or very unsatisfied.

   What interval scale would you assign to these terms so that its higher value means very satisfied?

   Rubric challenge $a_{3,1}$ base answer: Any interval decrements such as 4, 3, 2, 1 or 3, 2, 1, 0.

6. A program receives a square image as input and outputs a square image resized to the closest of 4 different pixel-sizes: 100, 1000, 10000, or 100000.

   If x is 2, 3, 4, or 5, then what function could calculate the pixel-size values: 100, 1000, 10000, and 100000.

   Rubric challenge $a_{3,3}$ base answer: Ten to the power of x.

7. An interval scale measures drowsiness and consists of incremental numbers: 0, 0.1, 0.2 and so forth up to 100.

   Does a measurement of 0 necessarily mean there is no feeling of drowsiness at all?

   Rubric challenge $a_{4,2}$ base answer: No, because the scale units are arbitrary.

8. The Celsius temperature scale shows 0 for when water freezes and 100 for when it boils

under normal atmospheric pressure.

What is true of all temperatures below the freezing point of water in the Celsius scale?

Rubric challenge $a_{4,4}$ base answer: They are negative values.

9. A rotational switch controls the brightness of a light and its position is measured by the numbers from 0 to 1000.

   What function could be used to calculate the minimum and maximum brightness in the range from 0 to 1?

   Rubric challenge $a_{5,1}$ base answer: The ratio of the switch's measurement of position to its maximum value of 1000.

10. A sensor measures pounds per square inch (psi) of pressure up to 30 with accuracy of .01 psi.

    How many digits are necessary to display the measurement with maximum accuracy?

    Rubric challenge $a_{5,3}$ base answer: 4.

11. A program receives natural (for example 1, 2, 3) numbers from 0 to 1000 as input and drives the rotation of a motor within the range of 180 angle degrees.

    How would you calculate the rotation with an accuracy of .1 angle degree given the input?

    Rubric challenge $a_{6,2}$ base answer: calculate the input value divided by the ratio of 1000 over 180 and output the result with only 1 decimal point.

12. A program receives natural (for example 1, 2, 3) numbers from 0 to 1023 as input.

    How would you calculate an output from -1 to 1 with accuracy of .1?

    Rubric challenge $a_{6,4}$ base answer: calculate the -1 plus the ratio of input value over 1023 divided by 2 and output the result with only 1 decimal point.

6.2.2 Quiz of Subsequent Computational Knowledge

1. An interval scale consists of the following set of numbers {3, 5, 7, 9, 11, 13}.

   What interval creates this scale?

   Rubric challenge $a_{1,2}$ base answer: 2.

2. A computation receives as input a natural (for example 1, 2, 3) number from 100 to 300 and outputs a proportional range of light brightness from 200 to 1000 Lumens.

   When the input value is 200, then how bright should the light be in Lumens?

   Rubric challenge $a_{1,4}$ base answer: 600.

3. A scale consists of incremental numbers: 10, 11, 13, 14 and so forth up to 50.

   If we give the scale an interval of .5, for example 10, 10.5, 11, 11.5 and so forth up to 50, will this make the scale more or less sensitive?

   Rubric challenge $a_{2,1}$ base answer: More sensitive.

4. An interval scale consists of a range of natural (for example 1, 2, 3) numbers from 100 to 300.

   If you decrease the sensitivity of this scale by .5, then what would be the first 3 scale steps after 100?

   Rubric challenge $a_{2,3}$ base answer: 101.5, 103, 104.5.

5. An interval scale consists of a range of natural (for example 1, 2, 3) numbers from 200 to 400.

   What would be an equivalent scale's maximum value if its minimum value is 1?

   Rubric challenge $a_{3,2}$ base answer: 201.

6. A program counts seconds, minutes, and hours per day to label time intervals.

   Define the limits of the interval scales that should be used to count seconds, minutes, and hours.

   Rubric challenge $a_{3,4}$ base answer: seconds 0 to 59, minutes 0 to 59, hours 0 to 23.

7. A computation measures the color temperature of a light bulb in Kelvin units to operate the light with 5 different color temperatures: 2000, 3000, 4000, 5500, and 6500.

   What should be the minimum and maximum values of an interval scale that switches between the different color temperatures? What should be the interval value of this scale?

   Rubric challenge $a_{4,1}$ base answer: minimum 2000, maximum 6500, interval 500.

8. A laboratory multimeter measures the voltage of direct current with accuracy of .0001 Volts.

   Is a display of 3-digits the most appropriate way to show the measurement value?

   Rubric challenge $a_{4,3}$ base answer: No, because the accuracy of measurement requires 4 digits.

9. A sound synthesizer receives a pitch value from 0 to 127, but has only 88 keyboard keys with each corresponding to a pitch.

   If key 1 corresponds to pitch value 20, then what would be the minimum and maximum values of a pitch value scale optimized for the number of keyboard keys?

   Rubric challenge $a_{5,2}$ base answer: 20 to 107.

10. A program operates continuously and stores natural (for example 1, 2, 3) numbers ranging from 0 to 1023.

    What would the program store if it received the number 1045?

    Rubric challenge $a_{5,4}$ base answer: 1023, because it is the closest value in the program's range.

11. A program receives natural (for example 1, 2, 3) numbers as input and drives the rotation of a motor within the range of 0 to 360 angle degrees.

    What is the optimal input range to drive the motor to all possible angle positions with accuracy of .1 angle degree?

    Rubric challenge $a_{6,1}$ base answer: 0 to 3600 or equivalent range.

12. A program receives natural (for example 1, 2, 3) numbers from 0 to 1000 as input and

drives the brightness of a light.

How would you calculate the program's output?

Rubric challenge $a_{6,3}$ base answer: by the ratio of input value over the maximum input value 1000.

7 Appendix B

7.1 Numerical Tables of Statistical Analysis

Table 18: Descriptive Statistics of Sample (duplicate of Table 11 for reference within Section 7)

T	**Stat**	**CK**	**Pre**	**Post**	$\Delta_{\mathbf{CK}}$	$\mathbf{Enj_1}$	$\mathbf{Enj_2}$	$\Delta_{\mathbf{Enj}}$	$\mathbf{Exc_1}$	$\mathbf{Exc_2}$	$\Delta_{\mathbf{Exc}}$	$\mathbf{M_E}$	$\mathbf{M_U}$	$\mathbf{M_S}$	$\mathbf{M_I}$	$\mathbf{T_A}$	$\mathbf{T_C}$	$\mathbf{T_E}$	$\mathbf{T_N}$	$\mathbf{T_O}$
1	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
1	MIN	.174	.139	.167		0.000	0.000		0.000	0.000		.167	.167	.167	.168	.338	.289	.082	.087	.407
1	MAX	.849	.917	.950		.950	1.000		1.000	1.000		1.000	.967	1.000	1.000	.680	.761	.691	.598	.764
1	MEAN	.560	.540	.579	.039	.383	.413	.031	.435	.371	-.064	.641	.422	.557	.522	.535	.561	.420	.409	.586
1	STD	.193	.222	.203		.300	.312		.322	.316		.210	.228	.255	.233	.089	.128	.157	.132	.097
2	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
2	MIN	.231	.139	.194		0.000	0.000		0.000	0.000		.167	.167	.167	.222	.395	.313	.202	.142	.369
2	MAX	.824	.833	.883		1.000	1.000		1.000	1.000		.887	.956	.843	.926	.743	.778	.782	.684	.800
2	MEAN	.575	.550	.599	.049	.485	.504	.020	.550	.421	-.129	.587	.471	.579	.574	.583	.546	.412	.407	.568
2	STD	.159	.180	.183		.293	.308		.295	.287		.189	.243	.177	.193	.088	.111	.142	.145	.129
3	N	30	30	30		30	30		30	30		29	30	30	30	30	30	30	30	30
3	MIN	.274	.222	.297		0.000	0.000		0.000	0.000		.168	.167	.167	.167	.128	.330	.084	.181	.306
3	MAX	.882	.992	.917		.905	1.000		1.000	1.000		.945	.723	.838	.901	.683	.800	.778	.708	.778
3	MEAN	.604	.603	.605	.002	.373	.369	-.003	.408	.331	-.078	.575	.346	.473	.447	.520	.568	.437	.420	.578
3	STD	.154	.187	.162		.285	.305		.311	.304		.204	.178	.237	.201	.127	.127	.167	.136	.126
4	N	30	30	30		30	30		30	30		30	30	30	30	30	30	30	30	30
4	MIN	.194	.139	.250		0.000	.105		0.000	0.000		.248	.213	.268	.268	.338	.290	.033	.160	.206
4	MAX	.888	.917	.883		1.000	1.000		1.000	1.000		1.000	.862	1.000	.920	.757	.786	.754	.711	.744
4	MEAN	.557	.521	.593	.072	.418	.558	.140	.505	.450	-.055	.596	.453	.668	.586	.571	.531	.412	.431	.549
4	STD	.169	.205	.168		.272	.234		.282	.251		.172	.168	.195	.162	.106	.124	.202	.180	.123

[1] Most values are standardized [0,1] and mean statistical values lower than .5 are indicated with red color. However, observation values (N) are natural numbers and difference values (Δ_{CK}, Δ_{Enj}, Δ_{Exc}) are normalized [-1,1].

Note: **T**= Treatment (4 is the control treatment);
Stat= Statistic;
CK= Total Computational Knowledge Score;
Pre= Score of Prior (before-treatment) Computational Knowledge;
Post= Score of Subsequent (after-treatment) Computational Knowledge;
$\Delta_{\mathbf{CK}}$= Subsequent minus Prior Computational Knowledge Score (difference);
$\mathbf{Enj_1}$= Measurement of Enjoyment before treatment;
$\mathbf{Enj_2}$= Measurement of Enjoyment after treatment;
$\Delta_{\mathbf{Enj}}$= After-treatment minus Before-treatment Enjoyment (difference);
$\mathbf{Exc_1}$= Measurement of Excitement before treatment;
$\mathbf{Exc_2}$= Measurement of Excitement after treatment;
$\Delta_{\mathbf{Exc}}$= After-treatment minus Before-treatment Excitement (difference);
$\mathbf{M_E}$= Index of Motivational Empowerment;
$\mathbf{M_U}$= Index of Motivational Usefulness;
$\mathbf{M_S}$= Index of Motivational Success;
$\mathbf{M_I}$= Index of Motivational Interest;
$\mathbf{T_A}$= Personality Index of Agreeableness;
$\mathbf{T_C}$= Personality Index of Conscientiousness;
$\mathbf{T_E}$= Personality Index of Extraversion;
$\mathbf{T_N}$= Personality Index of Neuroticism;
$\mathbf{T_O}$= Personality Index of Openess to experience.

Table 19: Descriptive Statistics of Subject Pool with more than .083 Δ_{CK}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
1	MIN	.242	.194	.289		0.000	0.000		0.000	0.000		.249	.167	.179	.173	.346	.408	.082	.087	.462
1	MAX	.808	.667	.950		.895	1.000		.950	1.000		1.000	.967	1.000	1.000	.612	.741	.691	.516	.764
1	MEAN	.549	.449	.650	**.201**	.316	.342	.026	.368	.356	-.012	.642	.399	.573	.511	.514	.620	.445	.357	.635
1	STD	.165	.153	.182		.321	.334		.343	.360		.241	.247	.262	.226	.070	.100	.209	.142	.088
2	N	12	12	12		12	12		12	12		12	12	12	12	12	12	12	12	12
2	MIN	.231	.139	.322		0.000	0.000		0.000	0.000		.208	.167	.251	.222	.445	.313	.202	.254	.370
2	MAX	.824	.764	.883		.760	.835		.865	.815		.887	.935	.778	.926	.743	.778	.698	.587	.800
2	MEAN	.544	.433	.654	**.221**	.395	.423	.028	.533	.353	-.180	.649	.503	.591	.600	.580	.536	.423	.430	.588
2	STD	.181	.185	.189		.272	.291		.299	.272		.192	.265	.157	.211	.095	.126	.170	.105	.118
3	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
3	MIN	.419	.222	.550		0.000	0.000		0.000	0.000		.168	.167	.167	.167	.128	.354	.253	.181	.348
3	MAX	.792	.750	.833		.755	.520		1.000	1.000		.618	.374	.721	.532	.683	.800	.651	.519	.778
3	MEAN	.580	.481	.678	**.196**	.201	.156	-.045	.397	.258	-.139	.438	.219	.327	.306	.530	.635	.503	.348	.614
3	STD	.115	.151	.088		.230	.160		.385	.333		.172	.076	.196	.116	.173	.145	.138	.119	.137
4	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
4	MIN	.194	.139	.250		0.000	.210		0.000	0.000		.333	.238	.319	.333	.389	.382	.248	.160	.457
4	MAX	.761	.639	.883		1.000	1.000		1.000	1.000		.884	.862	1.000	.920	.732	.786	.742	.695	.733
4	MEAN	.501	.388	.613	**.225**	.477	.630	.152	.537	.546	.009	.616	.534	.701	.641	.581	.577	.443	.345	.557
4	STD	.181	.179	.193		.308	.248		.270	.283		.133	.184	.210	.169	.109	.123	.151	.176	.085

Note: For labels and number scale information see Table 18.

Table 20: Descriptive Statistics of Subject Pool with less than .083 Δ_{CK}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
1	MIN	.236	.306	.167		0.000	.130		.165	.045		.398	.203	.227	.257	.448	.333	.203	.115	.524
1	MAX	.849	.917	.781		.950	.960		1.000	.800		.860	.828	.958	.829	.680	.761	.617	.537	.720
1	MEAN	.625	.718	.533	**-.186**	.459	.539	.080	.582	.350	-.232	.651	.399	.563	.508	.566	.540	.396	.443	.607
1	STD	.223	.230	.228		.315	.291		.323	.293		.135	.209	.260	.227	.076	.140	.128	.133	.073
2	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
2	MIN	.354	.499	.194		0.000	.015		0.000	0.000		.308	.167	.167	.229	.395	.406	.325	.165	.399
2	MAX	.764	.806	.722		1.000	1.000		1.000	.775		.805	.956	.843	.781	.648	.743	.782	.578	.775
2	MEAN	.567	.657	.477	**-.180**	.562	.647	.085	.600	.536	-.064	.597	.503	.578	.583	.566	.587	.441	.393	.538
2	STD	.143	.119	.173		.345	.330		.324	.301		.184	.254	.217	.186	.090	.105	.156	.189	.128
3	N	11	11	11		11	11		11	11		10	11	11	11	11	11	11	11	11
3	MIN	.424	.472	.367		0.000	.050		0.000	0.000		.385	.167	.229	.195	.236	.379	.084	.298	.306
3	MAX	.858	.992	.725		.905	1.000		1.000	1.000		.945	.723	.838	.901	.604	.718	.537	.708	.692
3	MEAN	.600	.680	.521	**-.160**	.436	.543	.108	.420	.452	.032	.680	.436	.575	.548	.475	.533	.342	.488	.559
3	STD	.138	.150	.136		.285	.345		.327	.356		.206	.213	.250	.222	.120	.118	.164	.142	.138
4	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
4	MIN	.368	.472	.264		.080	.105		.135	0.000		.274	.285	.576	.384	.338	.343	.089	.252	.206
4	MAX	.733	.833	.633		.725	.830		1.000	.610		1.000	.635	.892	.701	.757	.617	.754	.698	.744
4	MEAN	.587	.667	.507	**-.160**	.394	.530	.136	.476	.304	-.172	.659	.418	.706	.595	.574	.510	.499	.495	.537
4	STD	.123	.118	.131		.256	.284		.346	.255		.239	.159	.114	.117	.141	.111	.236	.151	.208

Note: For labels and number scale information see Table 18.

Table 21: Descriptive Statistics of Subject Pool with Positive Δ_{CK}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_{E}	M_{U}	M_{S}	M_{I}	T_{A}	T_{C}	T_{E}	T_{N}	T_{O}
1	N	18	18	18		18	18		18	18		18	18	18	18	18	18	18	18	18
1	MIN	.181	.152	.208		0.000	0.000		0.000	0.000		.167	.167	.167	.168	.338	.289	.082	.087	.455
1	MAX	.800	.682	.950		.895	1.000		.950	1.000		1.000	.967	1.000	1.000	.613	.741	.691	.598	.764
1	MEAN	.517	.436	.597	**.161**	.315	.314	-.001	.350	.336	-.014	.600	.400	.516	.480	.502	.567	.434	.387	.594
1	STD	.179	.163	.203		.297	.313		.308	.337		.235	.239	.262	.226	.085	.129	.179	.138	.102
2	N	18	18	18		18	18		18	18		18	18	18	18	18	18	18	18	18
2	MIN	.241	.152	.322		0.000	0.000		0.000	0.000		.208	.167	.251	.222	.445	.313	.202	.203	.370
2	MAX	.816	.803	.883		.875	1.000		1.000	1.000		.887	.935	.824	.926	.743	.778	.698	.684	.800
2	MEAN	.591	.508	.674	**.166**	.499	.512	.013	.585	.404	-.181	.633	.522	.628	.622	.587	.526	.406	.414	.593
2	STD	.167	.190	.160		.286	.305		.280	.290		.176	.232	.143	.190	.092	.108	.149	.126	.114
3	N	15	15	15		15	15		15	15		15	15	15	15	15	15	15	15	15
3	MIN	.242	.182	.297		0.000	0.000		0.000	0.000		.168	.167	.167	.167	.128	.354	.253	.181	.348
3	MAX	.877	.834	.917		.795	.670		1.000	1.000		.876	.585	.721	.667	.683	.800	.778	.600	.778
3	MEAN	.591	.522	.659	**.137**	.317	.245	-.072	.422	.246	-.175	.515	.283	.368	.374	.540	.613	.493	.369	.579
3	STD	.164	.186	.156		.271	.219		.318	.260		.196	.135	.188	.157	.134	.121	.138	.121	.132
4	N	19	19	19		19	19		19	19		19	19	19	19	19	19	19	19	19
4	MIN	.203	.152	.250		0.000	.210		0.000	0.000		.248	.230	.268	.268	.389	.290	.033	.160	.348
4	MAX	.751	.606	.883		1.000	1.000		1.000	1.000		.884	.862	1.000	.920	.732	.786	.742	.711	.733
4	MEAN	.504	.419	.590	**.171**	.408	.561	.152	.488	.487	-.001	.587	.475	.653	.579	.573	.548	.389	.395	.551
4	STD	.165	.170	.176		.295	.235		.264	.262		.146	.181	.233	.194	.103	.130	.196	.189	.095

Note: For labels and number scale information see Table 18.

Table 22: Descriptive Statistics of Subject Pool with Negative Δ_{CK}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_{E}	M_{U}	M_{S}	M_{I}	T_{A}	T_{C}	T_{E}	T_{N}	T_{O}
1	N	12	12	12		12	12		12	12		12	12	12	12	12	12	12	12	12
1	MIN	.232	.303	.167		0.000	.130		.165	.045		.398	.203	.227	.257	.448	.333	.203	.115	.407
1	MAX	.842	.909	.800		.950	.960		1.000	.800		.926	.828	.958	.829	.680	.761	.617	.564	.720
1	MEAN	.624	.697	.551	**-.146**	.485	.563	.078	.562	.424	-.138	.702	.456	.618	.584	.583	.552	.399	.441	.574
1	STD	.202	.211	.210		.287	.254		.311	.288		.153	.218	.244	.237	.073	.133	.119	.123	.092
2	N	12	12	12		12	12		12	12		12	12	12	12	12	12	12	12	12
2	MIN	.370	.424	.194		0.000	.015		0.000	0.000		.167	.167	.167	.229	.395	.395	.221	.142	.369
2	MAX	.790	.818	.764		1.000	1.000		1.000	.775		.805	.956	.843	.781	.659	.743	.782	.591	.800
2	MEAN	.551	.613	.488	**-.126**	.463	.493	.030	.497	.445	-.052	.519	.395	.505	.502	.577	.577	.422	.397	.531
2	STD	.149	.147	.163		.315	.327		.320	.294		.196	.250	.202	.182	.084	.112	.137	.175	.146
3	N	15	15	15		15	15		15	15		14	15	15	15	15	15	15	15	15
3	MIN	.409	.424	.367		0.000	0.000		0.000	0.000		.340	.167	.229	.195	.236	.330	.084	.298	.306
3	MAX	.869	.991	.833		.905	1.000		1.000	1.000		.945	.723	.838	.901	.655	.718	.707	.708	.714
3	MEAN	.617	.684	.551	**-.133**	.428	.493	.066	.395	.415	.020	.640	.410	.579	.520	.500	.522	.381	.472	.576
3	STD	.149	.154	.154		.297	.335		.313	.329		.198	.197	.239	.217	.120	.120	.179	.134	.124
4	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
4	MIN	.384	.515	.264		.080	.105		.120	0.000		.274	.213	.518	.384	.338	.320	.089	.199	.206
4	MAX	.883	.909	.858		.725	.830		1.000	.665		1.000	.635	.892	.701	.757	.625	.754	.698	.744
4	MEAN	.649	.703	.595	**-.108**	.416	.527	.112	.518	.364	-.154	.641	.420	.700	.593	.582	.512	.443	.484	.546
4	STD	.147	.132	.168		.243	.241		.333	.227		.206	.150	.110	.095	.112	.116	.223	.155	.175

Note: For labels and number scale information see Table 18.

Table 23: Descriptive Statistics of Subject Pool with Positive Δ_{Enj}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
1	MIN	.232	.272	.167		0.000	.130		.100	.045		.313	.168	.227	.261	.448	.382	.203	.087	.407
1	MAX	.842	.909	.950		.895	1.000		1.000	1.000		1.000	.967	.817	1.000	.680	.761	.691	.564	.720
1	MEAN	.591	.589	.593	.004	.365	.583	**.217**	.465	.544	.079	.682	.443	.550	.639	.564	.595	.415	.394	.596
1	STD	.166	.213	.189		.301	.294		.332	.304		.217	.229	.221	.210	.071	.107	.176	.168	.093
2	N	16	16	16		16	16		16	16		16	16	16	16	16	16	16	16	16
2	MIN	.241	.152	.194		0.000	.015		0.000	0.000		.167	.167	.167	.229	.455	.376	.221	.203	.370
2	MAX	.816	.743	.883		.815	1.000		1.000	1.000		.887	.850	.824	.926	.684	.707	.698	.587	.800
2	MEAN	.522	.493	.551	.058	.383	.583	**.201**	.504	.455	-.049	.634	.492	.578	.603	.588	.537	.418	.443	.544
2	STD	.170	.164	.216		.282	.301		.298	.320		.183	.246	.215	.221	.075	.080	.138	.120	.134
3	N	11	11	11		11	11		11	11		11	11	11	11	11	11	11	11	11
3	MIN	.242	.182	.297		0.000	.135		0.000	.090		.379	.198	.376	.323	.394	.330	.084	.181	.348
3	MAX	.730	.727	.758		.450	1.000		1.000	1.000		.881	.723	.838	.901	.626	.718	.707	.679	.714
3	MEAN	.539	.538	.539	.001	.181	.525	**.343**	.305	.410	.105	.676	.434	.574	.592	.509	.502	.406	.452	.564
3	STD	.137	.181	.151		.172	.331		.288	.333		.192	.181	.175	.189	.086	.133	.201	.145	.114
4	N	21	21	21		21	21		21	21		21	21	21	21	21	21	21	21	21
4	MIN	.203	.152	.250		0.000	.105		0.000	0.000		.248	.213	.268	.268	.338	.290	.033	.160	.206
4	MAX	.790	.818	.883		.720	.985		1.000	.910		1.000	.862	.954	.909	.757	.786	.754	.711	.714
4	MEAN	.533	.508	.558	.050	.320	.581	**.262**	.487	.458	-.030	.595	.454	.627	.586	.594	.549	.405	.444	.533
4	STD	.175	.204	.174		.234	.230		.308	.232		.190	.191	.199	.164	.113	.132	.218	.177	.124

Note: For labels and number scale information see Table 18.

Table 24: Descriptive Statistics of Subject Pool with Negative Δ_{Enj}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
1	MIN	.181	.152	.208		.250	0.000		.225	0.000		.249	.168	.168	.168	.338	.289	.385	.190	.455
1	MAX	.822	.900	.883		.950	.850		.885	.800		.860	.828	.958	.829	.667	.741	.667	.535	.764
1	MEAN	.605	.592	.618	.027	.610	.398	**-.212**	.629	.302	-.327	.627	.485	.682	.482	.518	.514	.476	.403	.589
1	STD	.224	.253	.218		.221	.278		.240	.301		.186	.264	.250	.257	.095	.154	.088	.105	.112
2	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
2	MIN	.396	.273	.508		.295	.110		.165	.120		.355	.167	.365	.351	.445	.313	.202	.142	.369
2	MAX	.815	.818	.833		.875	.680		.865	.630		.819	.935	.669	.792	.743	.671	.782	.684	.740
2	MEAN	.625	.581	.670	.090	.584	.323	**-.262**	.590	.332	-.259	.559	.436	.564	.535	.598	.527	.412	.379	.576
2	STD	.141	.189	.135		.195	.183		.244	.194		.168	.221	.101	.128	.098	.124	.176	.167	.104
3	N	15	15	15		15	15		15	15		14	15	15	15	15	15	15	15	15
3	MIN	.399	.333	.375		.235	0.000		0.000	0.000		.168	.167	.167	.168	.128	.395	.251	.201	.306
3	MAX	.877	.991	.917		.905	.850		.825	.775		.945	.600	.835	.623	.683	.775	.778	.708	.778
3	MEAN	.637	.646	.628	-.018	.533	.275	**-.258**	.456	.257	-.199	.500	.288	.419	.368	.510	.590	.450	.397	.583
3	STD	.164	.192	.172		.269	.262		.291	.245		.207	.147	.258	.160	.162	.110	.138	.141	.148
4	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
4	MIN	.503	.416	.542		.500	.270		.320	0.000		.274	.238	.429	.333	.417	.343	.325	.252	.463
4	MAX	.732	.727	.847		.790	.650		.665	.660		.673	.583	.892	.670	.578	.588	.684	.698	.744
4	MEAN	.622	.587	.658	.071	.655	.438	**-.217**	.533	.359	-.173	.571	.435	.722	.535	.501	.471	.510	.443	.624
4	STD	.089	.108	.132		.100	.142		.123	.265		.151	.116	.158	.132	.067	.088	.138	.202	.127

Note: For labels and number scale information see Table 18.

Table 25: Descriptive Statistics of Subject Pool with Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
1	MIN	.181	.152	.167		0.000	.250		.100	.415		.313	.168	.305	.492	.462	.451	.203	.087	.407
1	MAX	.800	.818	.950		.895	1.000		.950	1.000		1.000	.967	.817	1.000	.680	.761	.691	.564	.680
1	MEAN	.507	.479	.534	.055	.438	.676	.238	.449	.692	**.243**	.701	.490	.646	.737	.568	.590	.427	.394	.568
1	STD	.197	.210	.234		.328	.259		.306	.192		.203	.244	.152	.141	.074	.097	.179	.165	.094
2	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
2	MIN	.286	.242	.194		.165	.110		.165	.330		.366	.167	.365	.406	.488	.462	.288	.142	.420
2	MAX	.790	.818	.797		.730	.785		.785	.815		.791	.828	.824	.878	.682	.667	.698	.591	.698
2	MEAN	.546	.536	.556	.019	.414	.579	.166	.537	.649	**.113**	.613	.479	.603	.606	.586	.557	.454	.414	.568
2	STD	.183	.173	.244		.203	.268		.214	.161		.147	.255	.165	.164	.064	.062	.137	.161	.105
3	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
3	MIN	.409	.424	.367		0.000	.195		0.000	.135		.379	.167	.246	.371	.236	.330	.084	.330	.360
3	MAX	.852	.991	.850		.905	1.000		.700	1.000		.945	.723	.837	.901	.606	.718	.707	.708	.714
3	MEAN	.643	.683	.602	-.081	.375	.561	.186	.277	.438	**.161**	.658	.416	.548	.555	.466	.536	.405	.521	.561
3	STD	.153	.184	.158		.304	.283		.234	.281		.217	.182	.211	.175	.113	.139	.195	.124	.118
4	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
4	MIN	.232	.152	.306		0.000	.105		0.000	.155		.390	.230	.268	.269	.338	.343	.089	.160	.206
4	MAX	.732	.818	.847		.790	.985		.780	.910		.884	.862	.954	.909	.732	.786	.742	.651	.665
4	MEAN	.513	.478	.548	.071	.361	.607	.246	.311	.508	**.197**	.624	.511	.607	.604	.600	.564	.380	.392	.512
4	STD	.163	.208	.147		.305	.237		.259	.226		.137	.204	.214	.179	.108	.129	.198	.181	.124

Note: For labels and number scale information see Table 18.

Table 26: Descriptive Statistics of Subject Pool with Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
1	MIN	.371	.333	.406		0.000	0.000		.200	0.000		.249	.168	.168	.168	.338	.333	.300	.144	.455
1	MAX	.822	.900	.883		.950	.850		1.000	.800		.960	.828	.958	.829	.667	.741	.667	.537	.764
1	MEAN	.678	.688	.668	-.020	.501	.346	-.156	.671	.236	**-.435**	.630	.419	.569	.422	.525	.579	.466	.392	.633
1	STD	.127	.180	.141		.294	.259		.271	.277		.220	.262	.322	.237	.088	.133	.128	.141	.100
2	N	14	14	14		14	14		14	14		14	14	14	14	14	14	14	14	14
2	MIN	.241	.152	.322		.130	.115		.235	.105		.167	.167	.493	.275	.445	.313	.202	.165	.369
2	MAX	.816	.803	.883		1.000	1.000		1.000	.625		.819	.956	.843	.792	.743	.743	.782	.684	.800
2	MEAN	.590	.548	.631	.084	.563	.462	-.101	.637	.296	**-.341**	.553	.529	.630	.580	.587	.524	.404	.385	.585
2	STD	.168	.200	.170		.268	.280		.240	.173		.194	.226	.103	.158	.096	.118	.150	.136	.126
3	N	15	15	15		15	15		15	15		15	15	15	15	15	15	15	15	15
3	MIN	.242	.182	.297		.090	0.000		.125	0.000		.168	.167	.167	.168	.128	.445	.216	.181	.306
3	MAX	.877	.909	.917		.905	.670		.825	.570		.876	.639	.812	.667	.683	.775	.778	.600	.778
3	MEAN	.608	.594	.623	.030	.456	.268	-.189	.492	.229	**-.262**	.510	.329	.449	.404	.530	.599	.455	.351	.581
3	STD	.171	.181	.183		.268	.235		.253	.194		.190	.176	.243	.168	.143	.097	.150	.110	.148
4	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
4	MIN	.203	.152	.250		.045	.270		.500	0.000		.248	.213	.377	.268	.389	.290	.033	.214	.377
4	MAX	.790	.818	.800		.665	.810		1.000	.665		1.000	.635	.941	.701	.757	.717	.754	.711	.744
4	MEAN	.577	.565	.589	.024	.426	.486	.060	.670	.346	**-.325**	.560	.380	.681	.544	.548	.507	.458	.504	.583
4	STD	.158	.168	.176		.210	.200		.159	.229		.220	.120	.174	.138	.115	.124	.209	.169	.125

Note: For labels and number scale information see Table 18.

Table 27: Descriptive Statistics of Subject Pool with Positive Δ_{Enj} and Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	3	3	3		3	3		3	3		3	3	3	3	3	3	3	3	3
1	MIN	.563	.472	.500		0.000	.130		.200	.045		.398	.221	.227	.261	.500	.615	.300	.144	.573
1	MAX	.694	.889	.653		.340	.425		1.000	.525		.960	.655	.253	.536	.611	.709	.650	.537	.720
1	MEAN	.646	.694	.597	-.097	.182	.267	**.085**	.642	.213	**-.428**	.621	.368	.240	.378	.554	.651	.418	.394	.668
1	STD	.073	.210	.084		.171	.149		.406	.270		.299	.249	.013	.142	.056	.050	.201	.217	.082
2	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
2	MIN	.231	.139	.322		.130	.190		.235	.105		.167	.167	.493	.275	.455	.448	.292	.303	.455
2	MAX	.824	.764	.883		.785	.850		.830	.510		.738	.751	.754	.752	.656	.582	.475	.523	.800
2	MEAN	.536	.500	.572	.072	.353	.518	**.165**	.551	.260	**-.291**	.558	.489	.635	.569	.565	.490	.423	.433	.543
2	STD	.226	.234	.225		.257	.312		.249	.160		.229	.224	.114	.202	.087	.053	.075	.091	.145
3	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
3	MIN																			
3	MAX																			
3	MEAN	.486	.444	.528	.083	.190	.403	**.213**	.303	.188	**-.115**	.747	.392	.490	.599	.525	.559	.556	.282	.504
3	STD																			
4	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
4	MIN	.194	.139	.250		.045	.285		.500	0.000		.248	.213	.377	.268	.389	.290	.033	.214	.377
4	MAX	.799	.806	.792		.655	.810		1.000	.665		1.000	.635	.941	.701	.757	.717	.754	.711	.714
4	MEAN	.568	.570	.566	-.004	.347	.544	**.198**	.717	.401	**-.316**	.576	.379	.660	.567	.578	.521	.409	.494	.551
4	STD	.185	.192	.200		.203	.215		.166	.229		.247	.134	.168	.138	.120	.145	.226	.165	.116

Note: For labels and number scale information see Table 18.

Table 28: Descriptive Statistics of Subject Pool with Negative Δ_{Enj} and Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	1	1	1		1	1		1	1		1	1	1	1	1	1	1	1	1
1	MIN																			
1	MAX																			
1	MEAN																			
1	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.
2	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
2	MIN																			
2	MAX																			
2	MEAN	.667	.694	.640	-.054	.365	.175	**-.190**	.368	.480	**.113**	.478	.174	.417	.428	.614	.564	.483	.367	.532
2	STD																			
3	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
3	MIN																			
3	MAX																			
3	MEAN	.819	.936	.703	-.233	.795	.620	**-.175**	.398	.505	**.108**	.684	.324	.541	.519	.368	.536	.502	.564	.504
3	STD																			
4	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
4	MIN																			
4	MAX																			
4	MEAN	.674	.653	.694	.042	.758	.608	**-.150**	.465	.635	**.170**	.669	.543	.715	.624	.545	.465	.396	.278	.564
4	STD																			

Note: For labels and number scale information see Table 18.

Table 29: Descriptive Statistics of Subject Pool with both Positive Δ_{Enj} and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
1	MIN	.264	.250	.167		0.000	.250		.100	.415		.313	.168	.305	.492	.484	.451	.203	.087	.407
1	MAX	.808	.833	.950		.895	1.000		.950	1.000		1.000	.967	.817	1.000	.680	.761	.691	.564	.680
1	MEAN	.544	.517	.570	.053	.407	.678	**.271**	.434	.691	**.257**	.702	.466	.645	.739	.580	.601	.423	.388	.579
1	STD	.168	.183	.216		.332	.275		.321	.203		.215	.245	.162	.149	.068	.097	.189	.174	.092
2	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
2	MIN	.274	.222	.194		.165	.500		.260	.500		.505	.303	.444	.472	.488	.495	.288	.254	.420
2	MAX	.704	.667	.797		.730	.785		.785	.815		.791	.828	.824	.878	.682	.589	.698	.550	.698
2	MEAN	.506	.484	.527	.044	.430	.714	**.284**	.593	.706	**.113**	.658	.580	.665	.666	.576	.554	.444	.430	.580
2	STD	.180	.144	.271		.233	.109		.180	.110		.125	.204	.137	.144	.068	.034	.160	.123	.108
3	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
3	MIN	.433	.389	.367		0.000	.195		0.000	.135		.379	.207	.376	.378	.394	.330	.084	.330	.403
3	MAX	.742	.750	.733		.450	1.000		.550	1.000		.881	.723	.837	.901	.604	.718	.707	.679	.714
3	MEAN	.567	.595	.538	-.057	.219	.535	**.316**	.236	.434	**.198**	.640	.457	.569	.592	.475	.519	.377	.517	.589
3	STD	.109	.131	.137		.193	.316		.211	.301		.215	.186	.186	.187	.083	.140	.230	.122	.105
4	N	11	11	11		11	11		11	11		11	11	11	11	11	11	11	11	11
4	MIN	.222	.139	.306		0.000	.105		0.000	.155		.390	.230	.268	.269	.338	.387	.089	.160	.206
4	MAX	.733	.833	.664		.720	.985		.780	.910		.884	.862	.954	.909	.732	.786	.742	.651	.623
4	MEAN	.484	.446	.522	.076	.289	.607	**.318**	.283	.485	**.202**	.616	.505	.587	.600	.609	.581	.377	.412	.503
4	STD	.158	.211	.127		.273	.258		.266	.239		.149	.222	.229	.194	.115	.122	.215	.190	.125

Note: For labels and number scale information see Table 18.

Table 30: Descriptive Statistics of Subject Pool with both Negative Δ_{Enj} and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
1	MIN	.397	.389	.406		.250	0.000		.225	0.000		.249	.168	.168	.168	.338	.333	.385	.190	.455
1	MAX	.829	.908	.883		.950	.850		.885	.800		.860	.828	.958	.829	.667	.741	.667	.535	.764
1	MEAN	.692	.685	.699	.014	.638	.379	**-.259**	.683	.246	**-.437**	.635	.441	.710	.441	.513	.549	.487	.391	.618
1	STD	.147	.184	.155		.218	.298		.234	.301		.207	.284	.279	.276	.100	.148	.098	.118	.109
2	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
2	MIN	.379	.250	.508		.395	.115		.330	.120		.355	.302	.504	.351	.445	.313	.202	.165	.369
2	MAX	.822	.819	.833		.875	.680		.865	.625		.819	.935	.669	.792	.743	.671	.782	.684	.740
2	MEAN	.615	.552	.678	.126	.639	.359	**-.279**	.646	.294	**-.351**	.580	.501	.601	.561	.593	.518	.394	.383	.587
2	STD	.141	.189	.137		.175	.185		.217	.185		.174	.196	.068	.130	.109	.128	.195	.145	.105
3	N	12	12	12		12	12		12	12		12	12	12	12	12	12	12	12	12
3	MIN	.424	.389	.375		.235	0.000		.125	0.000		.168	.167	.167	.168	.128	.445	.253	.201	.306
3	MAX	.882	.916	.917		.905	.650		.825	.570		.757	.600	.812	.598	.683	.775	.778	.600	.778
3	MEAN	.620	.605	.635	.030	.505	.233	**-.271**	.503	.237	**-.266**	.469	.292	.414	.358	.529	.610	.458	.356	.587
3	STD	.159	.169	.176		.271	.226		.263	.214		.176	.147	.251	.153	.160	.096	.141	.111	.148
4	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
4	MIN	.482	.381	.558		.500	.270		.500	0.000		.274	.238	.429	.333	.417	.417	.392	.316	.469
4	MAX	.692	.667	.800		.665	.410		.665	.410		.635	.456	.892	.651	.578	.530	.684	.698	.744
4	MEAN	.597	.554	.640	.086	.604	.354	**-.250**	.566	.221	**-.345**	.521	.382	.726	.490	.479	.474	.566	.525	.654
4	STD	.086	.122	.110		.075	.060		.081	.200		.168	.098	.203	.140	.073	.054	.124	.200	.128

Note: For labels and number scale information see Table 18.

Table 31: Descriptive Statistics of Subject Pool with Positive Δ_{CK} and Negative Δ_{Enj}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_{E}	M_{U}	M_{S}	M_{I}	T_{A}	T_{C}	T_{E}	T_{N}	T_{O}
1	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
1	MIN	.174	.139	.208		.250	0.000		.225	0.000		.249	.168	.168	.168	.338	.289	.385	.190	.455
1	MAX	.775	.667	.883		.715	.655		.650	.700		.691	.714	.932	.719	.613	.741	.667	.506	.764
1	MEAN	.481	.417	.545	**.128**	.518	.266	**-.252**	.464	.219	-.245	.519	.398	.594	.399	.476	.524	.473	.378	.577
1	STD	.231	.192	.275		.220	.240		.189	.295		.181	.241	.281	.226	.098	.165	.112	.130	.142
2	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
2	MIN	.379	.250	.508		.395	.115		.455	.140		.355	.302	.504	.351	.445	.313	.202	.306	.548
2	MAX	.822	.819	.833		.875	.680		.865	.625		.819	.935	.669	.792	.743	.666	.600	.684	.740
2	MEAN	.632	.537	.727	**.190**	.660	.339	**-.321**	.742	.328	-.413	.611	.483	.606	.552	.613	.513	.340	.426	.624
2	STD	.162	.219	.121		.198	.214		.147	.200		.190	.228	.061	.148	.112	.123	.137	.132	.066
3	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
3	MIN	.424	.389	.458		.235	0.000		.225	0.000		.168	.167	.167	.168	.128	.498	.253	.201	.393
3	MAX	.882	.848	.917		.795	.520		.825	.570		.757	.537	.721	.598	.683	.775	.778	.600	.778
3	MEAN	.628	.575	.681	**.106**	.441	.207	**-.234**	.537	.208	-.329	.439	.271	.353	.363	.528	.635	.480	.365	.616
3	STD	.152	.165	.149		.259	.189		.261	.190		.194	.131	.233	.159	.173	.095	.153	.134	.147
4	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
4	MIN	.482	.381	.583		.500	.270		.500	0.000		.563	.238	.429	.333	.417	.442	.325	.305	.463
4	MAX	.743	.639	.847		.790	.565		.665	.660		.665	.502	.801	.670	.559	.588	.612	.695	.733
4	MEAN	.629	.547	.712	**.165**	.639	.393	**-.246**	.594	.360	-.234	.619	.400	.680	.495	.475	.517	.477	.427	.584
4	STD	.115	.114	.131		.122	.124		.069	.272		.043	.115	.172	.148	.065	.060	.139	.183	.139

Note: For labels and number scale information see Table 18.

Table 32: Descriptive Statistics of Subject Pool with Negative Δ_{CK} and Positive Δ_{Enj}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_{E}	M_{U}	M_{S}	M_{I}	T_{A}	T_{C}	T_{E}	T_{N}	T_{O}
1	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
1	MIN	.264	.361	.167		0.000	.130		.165	.045		.398	.221	.227	.261	.448	.382	.203	.115	.407
1	MAX	.849	.917	.781		.680	.960		1.000	.770		.926	.654	.802	.822	.680	.761	.617	.564	.720
1	MEAN	.602	.688	.516	**-.173**	.346	.571	**.226**	.415	.423	.008	.678	.384	.553	.608	.591	.583	.351	.433	.563
1	STD	.186	.210	.187		.269	.292		.317	.318		.192	.166	.239	.238	.085	.127	.131	.156	.108
2	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
2	MIN	.354	.389	.194		0.000	.015		0.000	0.000		.167	.167	.167	.229	.578	.549	.221	.425	.377
2	MAX	.536	.639	.433		.590	.785		.695	.755		.805	.641	.673	.723	.649	.707	.446	.578	.800
2	MEAN	.415	.494	.336	**-.159**	.221	.431	**.210**	.396	.394	-.002	.526	.309	.391	.396	.617	.598	.343	.504	.518
2	STD	.073	.096	.089		.243	.354		.361	.369		.266	.211	.217	.205	.026	.063	.083	.065	.179
3	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
3	MIN	.433	.472	.367		0.000	.195		0.000	.135		.385	.207	.422	.409	.394	.330	.084	.330	.403
3	MAX	.742	.750	.733		.450	1.000		1.000	1.000		.881	.723	.838	.901	.604	.718	.707	.679	.714
3	MEAN	.574	.631	.518	**-.113**	.219	.645	**.426**	.379	.544	.166	.708	.479	.635	.659	.502	.502	.368	.518	.595
3	STD	.107	.094	.130		.193	.326		.330	.350		.193	.184	.188	.181	.087	.144	.232	.121	.103
4	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
4	MIN	.368	.472	.264		.080	.105		.120	0.000		.390	.213	.518	.384	.338	.320	.089	.450	.206
4	MAX	.799	.833	.792		.655	.830		1.000	.665		1.000	.635	.770	.701	.757	.625	.754	.605	.714
4	MEAN	.626	.683	.570	**-.113**	.299	.504	**.204**	.551	.346	-.205	.698	.371	.659	.579	.597	.535	.445	.528	.496
4	STD	.147	.133	.172		.189	.279		.398	.229		.191	.146	.095	.110	.133	.108	.227	.062	.184

Note: For labels and number scale information see Table 18.

Table 33: Descriptive Statistics of Subject Pool with both Positive Δ_{CK} and Δ_{Enj}

T	**Stat**	**CK**	**Pre**	**Post**	Δ_{CK}	**Enj**$_1$	**Enj**$_2$	Δ_{Enj}	**Exc**$_1$	**Exc**$_2$	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
1	MIN	.386	.250	.522		0.000	.250		.100	.415		.313	.168	.253	.492	.484	.533	.228	.087	.536
1	MAX	.808	.667	.950		.895	1.000		.950	1.000		1.000	.967	.817	1.000	.564	.732	.691	.516	.710
1	MEAN	.577	.472	.682	**.210**	.388	.596	**.208**	.523	.684	.162	.687	.511	.547	.674	.533	.610	.491	.349	.634
1	STD	.155	.158	.161		.359	.324		.370	.237		.262	.286	.220	.188	.032	.087	.204	.184	.061
2	N	11	11	11		11	11		11	11		11	11	11	11	11	11	11	11	11
2	MIN	.231	.139	.322		.130	.190		.170	.105		.505	.168	.251	.446	.455	.376	.228	.203	.370
2	MAX	.824	.764	.883		.815	1.000		1.000	1.000		.887	.850	.824	.926	.684	.644	.698	.587	.703
2	MEAN	.570	.492	.648	**.156**	.456	.652	**.196**	.553	.483	-.070	.683	.575	.662	.697	.575	.510	.453	.415	.556
2	STD	.181	.192	.183		.277	.263		.270	.310		.115	.220	.160	.159	.087	.074	.147	.132	.116
3	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
3	MIN	.274	.222	.297		0.000	.135		0.000	.090		.379	.198	.376	.323	.401	.354	.341	.181	.348
3	MAX	.699	.639	.758		.290	.670		.350	.285		.876	.585	.557	.667	.626	.664	.651	.436	.659
3	MEAN	.476	.375	.576	**.201**	.115	.314	**.199**	.176	.175	-.001	.620	.356	.465	.475	.519	.503	.472	.336	.511
3	STD	.178	.190	.197		.123	.241		.156	.096		.203	.170	.081	.156	.097	.131	.130	.110	.128
4	N	13	13	13		13	13		13	13		13	13	13	13	13	13	13	13	13
4	MIN	.194	.139	.250		0.000	.310		0.000	.155		.248	.230	.268	.268	.389	.290	.033	.160	.348
4	MAX	.761	.639	.883		.720	.985		.780	.910		.884	.862	.954	.909	.732	.786	.742	.711	.699
4	MEAN	.475	.404	.545	**.141**	.307	.605	**.299**	.436	.506	.070	.561	.507	.609	.584	.604	.566	.371	.387	.552
4	STD	.175	.173	.186		.256	.203		.264	.227		.169	.206	.246	.195	.101	.146	.222	.201	.086

Note: For labels and number scale information see Table 18.

Table 34: Descriptive Statistics of Subject Pool with both Negative Δ_{CK} and Δ_{Enj}

T	**Stat**	**CK**	**Pre**	**Post**	Δ_{CK}	**Enj**$_1$	**Enj**$_2$	Δ_{Enj}	**Exc**$_1$	**Exc**$_2$	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.678	.722	.633		.500	.250		.750	.075		.708	.203	.546	.257	.512	.333	.396	.383	.556
1	MAX	.829	.908	.800		.950	.850		.885	.800		.860	.828	.958	.829	.667	.700	.532	.535	.715
1	MEAN	.760	.810	.710	**-.101**	.725	.563	-.163	.835	.406	**-.429**	.762	.593	.793	.585	.571	.502	.480	.435	.604
1	STD	.069	.076	.079		.185	.253		.062	.315		.068	.284	.181	.285	.069	.164	.063	.069	.074
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.536	.556	.517		.295	.110		.165	.120		.366	.167	.365	.406	.461	.395	.336	.142	.369
2	MAX	.799	.833	.764		.630	.430		.570	.630		.590	.576	.666	.650	.659	.671	.782	.591	.618
2	MEAN	.615	.646	.585	**-.061**	.470	.298	-.173	.363	.336	**-.026**	.481	.365	.501	.509	.575	.549	.521	.310	.504
2	STD	.125	.131	.120		.141	.151		.167	.215		.104	.221	.125	.107	.085	.142	.187	.208	.117
3	N	7	7	7		7	7		7	7		6	7	7	7	7	7	7	7	7
3	MIN	.424	.472	.375		.355	0.000		0.000	0.000		.340	.167	.229	.195	.236	.395	.251	.298	.306
3	MAX	.875	.992	.833		.905	.850		.730	.775		.945	.600	.835	.623	.655	.677	.537	.708	.692
3	MEAN	.647	.728	.567	**-.161**	.639	.354	-.285	.363	.314	**-.049**	.580	.308	.494	.374	.490	.537	.417	.433	.545
3	STD	.189	.200	.186		.258	.324		.316	.302		.211	.173	.281	.173	.159	.109	.119	.149	.150
4	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
4	MIN																			
4	MAX																			
4	MEAN	.608	.666	.550	**-.116**	.688	.530	-.158	.410	.358	**-.053**	.473	.507	.806	.615	.554	.380	.576	.475	.705
4	STD																			

Note: For labels and number scale information see Table 18.

Table 35: Descriptive Statistics of Subject Pool with Positive Δ_{CK} and Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj$_1$	Enj$_2$	Δ_{Enj}	Exc$_1$	Exc$_2$	Δ_{Exc}	M$_\mathrm{E}$	M$_\mathrm{U}$	M$_\mathrm{S}$	M$_\mathrm{I}$	T$_\mathrm{A}$	T$_\mathrm{C}$	T$_\mathrm{E}$	T$_\mathrm{N}$	T$_\mathrm{O}$
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.397	.389	.406		.250	0.000		.225	0.000		.249	.168	.168	.168	.338	.496	.385	.144	.455
1	MAX	.775	.667	.883		.660	.425		.725	.525		.960	.655	.932	.536	.550	.741	.667	.506	.764
1	MEAN	.592	.507	.676	**.170**	.476	.208	-.269	.541	.155	**-.386**	.589	.342	.512	.321	.464	.635	.534	.285	.656
1	STD	.157	.117	.204		.213	.174		.221	.251		.304	.230	.363	.163	.090	.112	.145	.161	.137
2	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
2	MIN	.231	.139	.322		.130	.115		.235	.105		.355	.302	.504	.351	.445	.313	.202	.303	.455
2	MAX	.824	.819	.883		.875	.850		.865	.625		.819	.935	.754	.792	.743	.666	.600	.684	.740
2	MEAN	.607	.529	.684	**.155**	.546	.413	-.133	.651	.276	**-.375**	.629	.518	.632	.588	.588	.495	.370	.420	.566
2	STD	.190	.225	.170		.268	.279		.224	.172		.151	.197	.078	.143	.104	.095	.120	.112	.090
3	N	10	10	10		10	10		10	10		10	10	10	10	10	10	10	10	10
3	MIN	.274	.250	.297		.090	0.000		.225	0.000		.168	.167	.167	.168	.128	.453	.253	.181	.348
3	MAX	.882	.848	.917		.795	.670		.825	.570		.876	.585	.721	.667	.683	.775	.778	.600	.778
3	MEAN	.599	.549	.650	**.102**	.391	.246	-.145	.490	.204	**-.287**	.501	.295	.381	.410	.527	.620	.495	.349	.594
3	STD	.178	.180	.182		.256	.225		.252	.174		.224	.156	.216	.175	.153	.103	.146	.132	.156
4	N	7	7	7		7	7		7	7		7	7	7	7	7	7	7	7	7
4	MIN	.194	.139	.250		.045	.270		.500	0.000		.248	.238	.377	.268	.389	.290	.033	.214	.469
4	MAX	.692	.583	.800		.665	.690		.665	.540		.699	.516	.941	.618	.626	.717	.612	.711	.733
4	MEAN	.543	.482	.604	**.122**	.376	.419	.043	.579	.321	**-.258**	.516	.371	.647	.462	.494	.518	.359	.462	.580
4	STD	.168	.168	.178		.232	.154		.066	.186		.166	.104	.218	.131	.093	.131	.214	.211	.099

Note: For labels and number scale information see Table 18.

Table 36: Descriptive Statistics of Subject Pool with Negative Δ_{CK} and Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj$_1$	Enj$_2$	Δ_{Enj}	Exc$_1$	Exc$_2$	Δ_{Exc}	M$_\mathrm{E}$	M$_\mathrm{U}$	M$_\mathrm{S}$	M$_\mathrm{I}$	T$_\mathrm{A}$	T$_\mathrm{C}$	T$_\mathrm{E}$	T$_\mathrm{N}$	T$_\mathrm{O}$
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.264	.361	.167		.060	.540		.165	.430		.620	.222	.507	.709	.603	.451	.203	.115	.407
1	MAX	.668	.833	.547		.680	.960		.700	.770		.926	.654	.802	.822	.680	.761	.617	.564	.630
1	MEAN	.498	.573	.423	**-.150**	.419	.738	.319	.374	.659	**.285**	.790	.445	.694	.787	.644	.614	.379	.387	.531
1	STD	.173	.199	.173		.281	.173		.234	.155		.143	.177	.133	.053	.033	.127	.177	.202	.114
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.354	.499	.194		.250	.110		.165	.330		.366	.167	.365	.406	.570	.462	.325	.142	.420
2	MAX	.799	.833	.764		.590	.785		.680	.755		.758	.641	.673	.723	.659	.667	.501	.591	.618
2	MEAN	.526	.600	.452	**-.148**	.393	.470	.078	.504	.604	**.100**	.559	.347	.488	.513	.605	.567	.408	.433	.519
2	STD	.197	.157	.246		.153	.345		.231	.190		.162	.223	.131	.143	.041	.085	.088	.203	.101
3	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
3	MIN	.433	.472	.367		0.000	.195		0.000	.135		.385	.167	.246	.409	.236	.330	.084	.330	.360
3	MAX	.858	.992	.733		.905	1.000		.700	1.000		.945	.723	.837	.901	.604	.718	.707	.708	.714
3	MEAN	.637	.706	.567	**-.139**	.391	.594	.204	.306	.478	**.172**	.683	.434	.586	.600	.457	.520	.413	.538	.574
3	STD	.151	.169	.147		.299	.293		.241	.303		.219	.201	.221	.167	.114	.150	.219	.134	.130
4	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
4	MIN	.553	.556	.542		.080	.105		.120	.180		.390	.285	.518	.384	.338	.343	.089	.252	.206
4	MAX	.733	.833	.633		.725	.830		.320	.610		.765	.583	.720	.578	.615	.617	.575	.593	.665
4	MEAN	.635	.694	.575	**-.119**	.299	.503	.204	.181	.376	**.195**	.625	.407	.635	.525	.515	.490	.347	.482	.478
4	STD	.077	.116	.041		.290	.313		.093	.177		.162	.146	.095	.094	.123	.113	.217	.156	.198

Note: For labels and number scale information see Table 18.

Table 37: Descriptive Statistics of Subject Pool with both Positive Δ_{CK} and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
1	MIN	.174	.139	.208		0.000	.250		.100	.415		.313	.168	.305	.492	.462	.498	.228	.087	.463
1	MAX	.808	.667	.950		.895	1.000		.950	1.000		1.000	.967	.817	1.000	.564	.732	.691	.516	.680
1	MEAN	.512	.417	.608	**.191**	.451	.634	**.183**	.498	.713	.215	.642	.521	.614	.704	.518	.575	.459	.399	.592
1	STD	.227	.209	.253		.381	.313		.358	.224		.227	.293	.168	.176	.041	.081	.188	.156	.079
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.274	.222	.325		.165	.500		.260	.500		.505	.303	.585	.583	.488	.495	.288	.254	.497
2	MAX	.704	.667	.797		.730	.780		.785	.815		.791	.828	.824	.878	.682	.579	.698	.515	.698
2	MEAN	.566	.472	.659	**.187**	.435	.689	**.254**	.570	.695	.125	.666	.610	.718	.700	.567	.547	.499	.395	.617
2	STD	.197	.184	.224		.266	.130		.225	.138		.128	.237	.106	.139	.084	.038	.174	.136	.095
3	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
3	MIN																			
3	MAX																			
3	MEAN	.666	.590	.742	**.151**	.313	.428	**.115**	.163	.280	.118	.555	.346	.396	.374	.503	.597	.374	.449	.510
3	STD																			
4	N	9	9	9		9	9		9	9		9	9	9	9	9	9	9	9	9
4	MIN	.222	.139	.306		0.000	.405		0.000	.155		.424	.230	.268	.269	.544	.387	.150	.160	.348
4	MAX	.743	.639	.847		.790	.985		.780	.910		.884	.862	.954	.909	.732	.786	.742	.651	.623
4	MEAN	.459	.381	.536	**.155**	.388	.653	**.265**	.368	.566	.198	.623	.557	.594	.638	.637	.596	.394	.351	.527
4	STD	.164	.161	.177		.324	.198		.292	.228		.136	.216	.254	.200	.082	.128	.201	.185	.086

Note: For labels and number scale information see Table 18.

Table 38: Descriptive Statistics of Subject Pool with both Negative Δ_{CK} and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O
1	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
1	MIN	.678	.722	.500		0.000	.130		.200	.045		.398	.203	.227	.257	.500	.333	.300	.383	.556
1	MAX	.829	.908	.800		.950	.850		1.000	.800		.860	.828	.958	.829	.667	.700	.532	.537	.720
1	MEAN	.736	.809	.663	**-.146**	.518	.438	-.080	.757	.290	**-.467**	.658	.470	.606	.490	.566	.542	.421	.463	.618
1	STD	.065	.079	.104		.358	.278		.285	.303		.172	.291	.321	.267	.064	.141	.104	.070	.077
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.407	.431	.383		.265	.410		.330	.120		.167	.167	.493	.275	.461	.395	.336	.165	.369
2	MAX	.653	.750	.556		1.000	1.000		1.000	.510		.545	.956	.843	.781	.648	.743	.782	.516	.800
2	MEAN	.547	.594	.499	**-.094**	.604	.584	-.020	.603	.348	**-.255**	.361	.559	.627	.559	.585	.598	.487	.297	.632
2	STD	.105	.135	.079		.305	.280		.310	.189		.162	.323	.164	.215	.085	.151	.201	.167	.200
3	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
3	MIN	.424	.472	.375		.375	0.000		.125	.040		.340	.199	.301	.198	.305	.445	.216	.298	.306
3	MAX	.875	.916	.833		.905	.650		.730	.560		.636	.639	.812	.567	.655	.654	.537	.419	.661
3	MEAN	.626	.683	.568	**-.115**	.587	.311	-.276	.495	.281	**-.214**	.529	.395	.585	.391	.536	.557	.375	.354	.555
3	STD	.175	.164	.193		.266	.277		.287	.242		.115	.213	.257	.173	.137	.076	.136	.056	.143
4	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
4	MIN	.368	.472	.264		.225	.285		.500	0.000		.274	.213	.576	.507	.548	.320	.399	.450	.377
4	MAX	.799	.806	.792		.655	.810		1.000	.665		1.000	.635	.892	.701	.757	.625	.754	.698	.744
4	MEAN	.612	.667	.558	**-.109**	.455	.515	.060	.790	.326	**-.464**	.666	.396	.737	.636	.645	.509	.576	.543	.594
4	STD	.167	.127	.207		.190	.225		.191	.293		.271	.162	.114	.077	.084	.134	.158	.106	.177

Note: For labels and number scale information see Table 18.

Table 39: Descriptive Statistics of Subject Pool with Positive Δ_{CK}, Positive Δ_{Enj}, and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	5	5	5		5	5		5	5		5	5	5	5	5	5	5	5	5
1	MIN	.386	.250	.522		0.000	.250		.100	.415		.313	.168	.305	.492	.484	.533	.228	.087	.536
1	MAX	.808	.667	.950		.895	1.000		.950	1.000		1.000	.967	.817	1.000	.564	.732	.691	.516	.680
1	MEAN	.580	.472	.688	**.216**	.398	.630	**.232**	.482	.716	**.234**	.632	.482	.606	.701	.529	.590	.459	.389	.618
1	STD	.174	.177	.179		.401	.350		.398	.250		.252	.310	.186	.196	.035	.080	.211	.172	.053
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.274	.222	.325		.165	.500		.260	.500		.505	.303	.585	.583	.488	.495	.288	.254	.497
2	MAX	.704	.667	.797		.730	.780		.785	.815		.791	.828	.824	.878	.682	.579	.698	.515	.698
2	MEAN	.566	.472	.659	**.187**	.435	.689	**.254**	.570	.695	**.125**	.666	.610	.718	.700	.567	.547	.499	.395	.617
2	STD	.197	.184	.224		.266	.130		.225	.138		.128	.237	.106	.139	.084	.038	.174	.136	.095
3	N	1	1	1		1	1		1	1		1	1	1	1	1	1	1	1	1
3	MIN																			
3	MAX																			
3	MEAN																			
3	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.
4	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
4	MIN	.222	.139	.306		0.000	.405		0.000	.155		.424	.230	.268	.269	.544	.387	.150	.160	.348
4	MAX	.621	.583	.664		.720	.985		.780	.910		.884	.862	.954	.909	.732	.786	.742	.651	.623
4	MEAN	.423	.349	.498	**.149**	.338	.664	**.326**	.338	.554	**.216**	.618	.564	.580	.635	.647	.597	.403	.357	.535
4	STD	.134	.137	.142		.307	.209		.297	.241		.144	.229	.268	.214	.082	.137	.214	.196	.088

Note: For labels and number scale information see Table 18.

Table 40: Descriptive Statistics of Subject Pool with Positive Δ_{CK}, Positive Δ_{Enj}, and Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	1	1	1		1	1		1	1		1	1	1	1	1	1	1	1	1
1	MIN																			
1	MAX																			
1	MEAN																			
1	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.
2	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
2	MIN	.231	.139	.322		.130	.190		.235	.105		.562	.430	.536	.446	.455	.448	.292	.303	.455
2	MAX	.824	.764	.883		.785	.850		.830	.320		.738	.751	.754	.752	.656	.481	.475	.523	.492
2	MEAN	.568	.517	.619	**.102**	.375	.524	**.149**	.515	.198	**-.318**	.656	.570	.671	.642	.551	.467	.417	.412	.478
2	STD	.247	.266	.230		.291	.360		.272	.090		.076	.153	.094	.136	.093	.014	.085	.091	.016
3	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
3	MIN																			
3	MAX																			
3	MEAN	.486	.444	.528	**.083**	.190	.403	**.213**	.303	.188	**-.115**	.747	.392	.490	.599	.525	.559	.556	.282	.504
3	STD																			
4	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
4	MIN	.194	.139	.250		.045	.310		.500	.160		.248	.251	.377	.268	.389	.290	.033	.214	.489
4	MAX	.656	.583	.756		.415	.690		.650	.540		.699	.516	.941	.618	.626	.717	.396	.711	.629
4	MEAN	.506	.456	.556	**.100**	.218	.483	**.265**	.573	.368	**-.205**	.450	.374	.629	.481	.530	.536	.232	.458	.547
4	STD	.211	.212	.217		.156	.180		.063	.170		.201	.115	.254	.159	.111	.178	.181	.250	.059

Note: For labels and number scale information see Table 18.

Table 41: Descriptive Statistics of Subject Pool with Positive Δ_{CK}, Negative Δ_{Enj}, and Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	MIN																			
1	MAX																			
1	MEAN																			
1	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.
2	N																			
2	MIN																			
2	MAX																			
2	MEAN																			
2	STD																			
3	N																			
3	MIN																			
3	MAX																			
3	MEAN																			
3	STD																			
4	N	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	MIN																			
4	MAX																			
4	MEAN																			
4	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.

Note: For labels and number scale information see Table 18.

Table 42: Descriptive Statistics of Subject Pool with Positive Δ_{CK}, Negative Δ_{Enj}, and Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	3	3	3		3	3		3	3		3	3	3	3	3	3	3	3	3
1	MIN	.397	.389	.406		.250	0.000		.225	0.000		.249	.168	.168	.168	.338	.496	.385	.190	.455
1	MAX	.775	.667	.883		.660	.205		.650	.095		.680	.373	.932	.353	.495	.741	.667	.506	.764
1	MEAN	.601	.519	.684	**.166**	.522	.135	**-.387**	.480	.032	**-.448**	.465	.238	.599	.249	.435	.610	.495	.332	.637
1	STD	.191	.140	.249		.235	.117		.225	.055		.215	.117	.391	.094	.085	.123	.150	.160	.162
2	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
2	MIN	.379	.250	.508		.395	.115		.455	.140		.355	.302	.504	.351	.445	.313	.202	.306	.548
2	MAX	.822	.819	.833		.875	.680		.865	.625		.819	.935	.669	.792	.743	.666	.600	.684	.740
2	MEAN	.632	.537	.727	**.190**	.660	.339	**-.321**	.742	.328	**-.413**	.611	.483	.606	.552	.613	.513	.340	.426	.624
2	STD	.162	.219	.121		.198	.214		.147	.200		.190	.228	.061	.148	.112	.123	.137	.132	.066
3	N	8	8	8		8	8		8	8		8	8	8	8	8	8	8	8	8
3	MIN	.424	.389	.458		.235	0.000		.225	0.000		.168	.167	.167	.168	.128	.498	.253	.201	.393
3	MAX	.882	.848	.917		.795	.520		.825	.570		.757	.537	.721	.598	.683	.775	.778	.600	.778
3	MEAN	.628	.575	.681	**.106**	.441	.207	**-.234**	.537	.208	**-.329**	.439	.271	.353	.363	.528	.635	.480	.365	.616
3	STD	.152	.165	.149		.259	.189		.261	.190		.194	.131	.233	.159	.173	.095	.153	.134	.147
4	N	3	3	3		3	3		3	3		3	3	3	3	3	3	3	3	3
4	MIN	.482	.381	.583		.500	.270		.500	0.000		.563	.238	.429	.333	.417	.442	.392	.316	.469
4	MAX	.692	.583	.800		.665	.380		.665	.410		.635	.456	.801	.554	.491	.530	.612	.695	.733
4	MEAN	.591	.516	.667	**.151**	.588	.335	**-.253**	.588	.260	**-.328**	.604	.366	.670	.437	.447	.494	.527	.467	.624
4	STD	.105	.117	.117		.083	.058		.083	.226		.037	.114	.209	.111	.039	.046	.118	.201	.138

Note: For labels and number scale information see Table 18.

Table 43: Descriptive Statistics of Subject Pool with Negative Δ_{CK}, Positive Δ_{Enj}, and Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.264	.361	.167		.060	.540		.165	.430		.620	.222	.507	.709	.603	.451	.203	.115	.407
1	MAX	.668	.833	.547		.680	.960		.700	.770		.926	.654	.802	.822	.680	.761	.617	.564	.630
1	MEAN	.498	.573	.423	**-.150**	.419	.738	**.319**	.374	.659	**.285**	.790	.445	.694	.787	.644	.614	.379	.387	.531
1	STD	.173	.199	.173		.281	.173		.234	.155		.143	.177	.133	.053	.033	.127	.177	.202	.114
2	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
2	MIN																			
2	MAX																			
2	MEAN	.385	.507	.264	**-.243**	.420	.765	**.345**	.640	.728	**.088**	.641	.520	.559	.598	.595	.569	.333	.500	.507
2	STD																			
3	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
3	MIN	.433	.472	.367		0.000	.195		0.000	.135		.385	.207	.422	.409	.394	.330	.084	.330	.403
3	MAX	.742	.750	.733		.450	1.000		.550	1.000		.881	.723	.837	.901	.604	.718	.707	.679	.714
3	MEAN	.576	.630	.522	**-.107**	.256	.586	**.330**	.275	.468	**.193**	.683	.471	.602	.627	.487	.515	.383	.530	.597
3	STD	.117	.103	.142		.183	.314		.201	.314		.199	.200	.181	.176	.084	.153	.251	.128	.112
4	N	3	3	3		3	3		3	3		3	3	3	3	3	3	3	3	3
4	MIN	.553	.556	.550		.080	.105		.120	.180		.390	.285	.518	.384	.338	.495	.089	.526	.206
4	MAX	.733	.833	.633		.225	.830		.150	.375		.765	.472	.705	.571	.615	.617	.575	.593	.570
4	MEAN	.645	.704	.586	**-.118**	.157	.453	**.297**	.135	.298	**.163**	.610	.348	.607	.508	.510	.539	.307	.559	.415
4	STD	.090	.140	.043		.073	.363		.015	.104		.195	.107	.094	.107	.150	.068	.247	.034	.188

Note: For labels and number scale information see Table 18.

Table 44: Descriptive Statistics of Subject Pool with Negative Δ_{CK}, Positive Δ_{Enj}, and Negative Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
1	MIN																			
1	MAX																			
1	MEAN	.688	.806	.569	**-.236**	.103	.188	**.085**	.600	.058	**-.543**	.451	.225	.234	.299	.555	.622	.302	.519	.646
1	STD																			
2	N	1	1	1		1	1		1	1		1	1	1	1	1	1	1	1	1
2	MIN																			
2	MAX																			
2	MEAN																			
2	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.
3	MIN																			
3	MAX																			
3	MEAN																			
3	STD																			
4	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
4	MIN	.368	.472	.264		.225	.285		.750	0.000		.568	.213	.576	.507	.548	.320	.399	.450	.377
4	MAX	.799	.806	.792		.655	.810		1.000	.665		1.000	.635	.770	.701	.757	.625	.754	.605	.714
4	MEAN	.612	.667	.558	**-.109**	.406	.541	**.135**	.863	.381	**-.481**	.764	.387	.698	.632	.661	.532	.550	.505	.557
4	STD	.193	.147	.239		.180	.251		.116	.307		.184	.185	.086	.088	.086	.143	.169	.072	.180

Note: For labels and number scale information see Table 18.

Table 45: Descriptive Statistics of Subject Pool with Negative Δ_{CK}, Negative Δ_{Enj}, and Positive Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.264	.361	.167		.060	.540		.165	.430		.620	.222	.507	.709	.603	.451	.203	.115	.407
1	MAX	.668	.833	.547		.680	.960		.700	.770		.926	.654	.802	.822	.680	.761	.617	.564	.630
1	MEAN	.498	.573	.423	**-.150**	.419	.738	**.319**	.374	.659	**.285**	.790	.445	.694	.787	.644	.614	.379	.387	.531
1	STD	.173	.199	.173		.281	.173		.234	.155		.143	.177	.133	.053	.033	.127	.177	.202	.114
2	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
2	MIN																			
2	MAX																			
2	MEAN	.385	.507	.264	**-.243**	.420	.765	**.345**	.640	.728	**.088**	.641	.520	.559	.598	.595	.569	.333	.500	.507
2	STD																			
3	N	6	6	6		6	6		6	6		6	6	6	6	6	6	6	6	6
3	MIN	.433	.472	.367		0.000	.195		0.000	.135		.385	.207	.422	.409	.394	.330	.084	.330	.403
3	MAX	.742	.750	.733		.450	1.000		.550	1.000		.881	.723	.837	.901	.604	.718	.707	.679	.714
3	MEAN	.576	.630	.522	**-.107**	.256	.586	**.330**	.275	.468	**.193**	.683	.471	.602	.627	.487	.515	.383	.530	.597
3	STD	.117	.103	.142		.183	.314		.201	.314		.199	.200	.181	.176	.084	.153	.251	.128	.112
4	N	3	3	3		3	3		3	3		3	3	3	3	3	3	3	3	3
4	MIN	.553	.556	.550		.080	.105		.120	.180		.390	.285	.518	.384	.338	.495	.089	.526	.206
4	MAX	.733	.833	.633		.225	.830		.150	.375		.765	.472	.705	.571	.615	.617	.575	.593	.570
4	MEAN	.645	.704	.586	**-.118**	.157	.453	**.297**	.135	.298	**.163**	.610	.348	.607	.508	.510	.539	.307	.559	.415
4	STD	.090	.140	.043		.073	.363		.015	.104		.195	.107	.094	.107	.150	.068	.247	.034	.188

Note: For labels and number scale information see Table 18.

Table 46: Descriptive Statistics of Subject Pool with Negative Δ_{CK}, Δ_{Enj}, and Δ_{Exc}

T	Stat	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	$\mathrm{M_E}$	$\mathrm{M_U}$	$\mathrm{M_S}$	$\mathrm{M_I}$	$\mathrm{T_A}$	$\mathrm{T_C}$	$\mathrm{T_E}$	$\mathrm{T_N}$	$\mathrm{T_O}$
1	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
1	MIN	.678	.722	.633		.500	.250		.750	.075		.708	.203	.546	.257	.512	.333	.396	.383	.556
1	MAX	.829	.908	.800		.950	.850		.885	.800		.860	.828	.958	.829	.667	.700	.532	.535	.715
1	MEAN	.760	.810	.710	**-.101**	.725	.563	**-.163**	.835	.406	**-.429**	.762	.593	.793	.585	.571	.502	.480	.435	.604
1	STD	.069	.076	.079		.185	.253		.062	.315		.068	.284	.181	.285	.069	.164	.063	.069	.074
2	N	2	2	2		2	2		2	2		2	2	2	2	2	2	2	2	2
2	MIN																			
2	MAX																			
2	MEAN	.563	.597	.529	**-.068**	.575	.420	**-.155**	.358	.193	**-.165**	.484	.556	.586	.590	.535	.533	.559	.253	.476
2	STD																			
3	N	4	4	4		4	4		4	4		4	4	4	4	4	4	4	4	4
3	MIN	.424	.472	.375		.375	0.000		.125	.040		.340	.199	.301	.198	.305	.445	.258	.298	.306
3	MAX	.875	.916	.833		.905	.650		.730	.560		.636	.600	.812	.562	.655	.654	.537	.405	.629
3	MEAN	.605	.667	.544	**-.123**	.631	.286	**-.345**	.436	.296	**-.140**	.529	.335	.537	.347	.532	.558	.415	.338	.529
3	STD	.195	.184	.213		.285	.314		.294	.277		.133	.189	.270	.164	.158	.087	.119	.050	.150
4	N	1	1	1		1	1		1	1		1	1	1	1	1	1	1	1	1
4	MIN																			
4	MAX																			
4	MEAN																			
4	STD	.	.	.		.	.		.	.		.	.	.	.	.	.	.	.	.

Note: For labels and number scale information see Table 18.

Table 47: Descriptive Statistics - Correlation Table of Sample Variables

Stat	Var	CK	Pre	Post	Δ_{CK}	Enj_1	Enj_2	Δ_{Enj}	Exc_1	Exc_2	Δ_{Exc}	M_E	M_U	M_S	M_I	T_A	T_C	T_E	T_N	T_O	Age	Q_t	$PreQ_t$	$PostQ_t$	Dur
MEAN		.574	.554	.594	.040	.414	.461	.047	.475	.393	-.081	.600	.423	.569	.532	.552	.552	.420	.417	.570	26.896	.377	.415	.338	2881
STD		.168	.199	.178	.171	.287	.297	.283	.304	.290	.292	.193	.210	.226	.204	.105	.122	.166	.148	.118	7.728	.136	.147	.137	1070
N		120	120	120	120	120	120	120	120	120	120	119	120	120	120	120	120	120	120	120	115	120	120	120	120
CORR	**CK**	1																							
CORR	**Pre**	**.905**	1																						
Prob		$p > .0001$																							
CORR	**Post**	**.879**	**.591**	1																					
Prob		$p > .0001$	$> .0001$																						
CORR	Δ_{CK}	-.138	**-.547**	**.351**	1																				
Prob		$p = .1318$	$> .0001$	$> .0001$																					
CORR	Enj_1	**.325**	**.320**	**.256**	-.106	1																			
Prob		**$p = .0003$**	**=.0004**	**=.0048**	=.2476																				
CORR	Enj_2	.051	.107	-.024	**-.149**	**.532**	1																		
Prob		$p = .5834$	=.245	=.7943	**=.104**	> .0001																			
CORR	Δ_{Enj}	-.277	**-.213**	**-.285**	-.049	**-.456**	**.510**	1																	
Prob		$p = .0022$	**=.0195**	**=.0016**	=.5972	> .0001	> .0001																		
CORR	Exc_1	**.260**	**.233**	**.231**	-.030	**.629**	**.466**	-.149	1																
Prob		**$p = .0041$**	**=.0105**	**=.011**	=.7435	> .0001	> .0001	=.1043																	
CORR	Exc_2	.065	.065	.050	-.024	**.434**	**.759**	**.357**	**.518**	1															
Prob		$p = .4831$	=.482	=.5898	=.7976	> .0001	> .0001	> .0001	> .0001																
CORR	Δ_{Exc}	**-.207**	**-.178**	**-.191**	.008	**-.223**	**.270**	**.510**	**-.526**	**.455**	1														
Prob		**$p = .0236$**	**=.0519**	**=.0362**	=.9318	**=.0142**	**=.0029**	> .0001	> .0001	> .0001															
CORR	M_E	-.050	-.018	-.074	-.056	**.190**	**.357**	**.181**	**.169**	**.287**	.109	1													
Prob		$p = .5894$	=.8426	=.4227	=.5486	**=.039**	> .0001	**=.0485**	**=.0663**	**=.0016**	=.2369														
CORR	M_U	-.054	-.061	-.033	.036	**.430**	**.603**	**.197**	**.378**	**.508**	.112	**.414**	1												
Prob		$p = .56$	=.5087	=.7169	=.6961	> .0001	> .0001	**=.0314**	> .0001	> .0001	=.2231	> .0001													
CORR	M_S	.129	.110	.120	-.003	**.536**	**.579**	.065	**.462**	**.438**	-.046	**.417**	**.59**	1											
Prob		$p = .161$	=.2315	=.1905	=.9748	> .0001	> .0001	=.482	> .0001	> .0001	=.6187	> .0001	> .0001												
CORR	M_I	-.047	-.045	-.039	.011	**.386**	**.787**	**.435**	**.375**	**.661**	**.267**	**.485**	**.75**	**.609**	1										
Prob		$p = .6071$	=.6261	=.6695	=.9023	> .0001	> .0001	> .0001	> .0001	> .0001	**=.0031**	> .0001	> .0001	> .0001											
CORR	T_A	**-.171**	**-.185**	-.116	.094	-.015	**.156**	**.179**	**.213**	.112	-.110	.088	**.1756**	.056	**.238**	1									
Prob		**$p = .0619$**	**=.0431**	=.2059	=.3065	=.8718	**=.0896**	**=.0508**	**=.0198**	=.2251	=.2303	=.3427	**=.055**	=.5471	**=.0089**										
CORR	T_C	-.038	-.075	.011	.098	-.069	-.060	.007	-.061	.019	.083	**-.172**	**-.16**	**-.211**	-.116	.109	1								
Prob		$p = .6764$	=.4164	=.9052	=.2853	=.4535	=.5167	=.9366	=.5072	=.8366	=.37	**=.0615**	**=.0801**	**=.0206**	=.2059	=.2375									
CORR	T_E	-.116	-.135	-.069	.085	.098	-.007	-.107	.114	.048	-.071	.017	.0392	.092	.053	.094	.052	1							
Prob		$p = .2066$	=.1426	=.4546	=.3568	=.2879	=.9405	=.2465	=.217	=.605	=.4426	=.8552	=.6708	=.3198	=.5686	=.3081	=.5742								
CORR	T_N	-.049	.045	-.143	**-.200**	**-.290**	**-.183**	.102	**-.271**	**-.266**	.017	.030	**-.242**	-.096	-.145	**-.169**	**-.260**	**-.266**	1						
Prob		$p = .5947$	=.6284	=.12	**=.0286**	**=.0013**	**=.0454**	=.2676	**=.0028**	**=.0033**	=.8496	=.7461	**=.0079**	=.2969	=.1141	**=.0651**	**=.0041**	**=.0033**							
CORR	T_O	.092	.033	.136	.103	**.205**	.023	**-.184**	**.268**	-.018	**-.297**	-.148	.0692	.125	-.030	.107	.133	**.173**	-.177	1					
Prob		$p = .3196$	=.7211	=.1374	=.2614	**=.0245**	=.8012	**=.0441**	**=.0031**	=.8438	**=.001**	=.1092	=.4529	=.1725	=.7471	=.2463	=.1461	**=.0583**	=.0536						
CORR	**Age**	-.019	-.125	.105	**.255**	.113	.013	-.102	.151	-.027	**-.184**	-.060	-.029	.032	-.039	-.087	**.330**	.089	**-.265**	**.192**	1				
Prob		$p = .8439$	=.1839	=.2631	**=.0059**	=.2279	=.8941	=.2758	=.1064	=.7755	**=.049**	=.5289	=.7548	=.7323	=.6804	=.3575	**=.0003**	=.345	**=.0042**	**=.0398**					
CORR	Q_t	**.245**	**.259**	**.173**	-.121	**.202**	**.227**	.033	**.272**	**.224**	-.061	-.040	**.3306**	**.157**	**.273**	**.173**	.058	-.085	-.135	**.195**	.023	1			
Prob		**$p = .007$**	**=.0043**	**=.0581**	=.1886	**=.0267**	**=.0129**	=.7238	**=.0026**	**=.0141**	=.5081	=.6675	**=.0002**	**=.0876**	**=.0025**	**=.0594**	=.5272	=.3549	=.1407	**=.0329**	=.8049				
CORR	$PreQ_t$	**.247**	**.270**	**.164**	-.143	**.184**	**.200**	.023	**.276**	**.194**	-.094	-.052	**.3092**	.151	**.275**	**.159**	-.031	-.058	-.088	**.175**	-.086	**.961**	1		
Prob		**$p = .0066$**	**=.0029**	**=.0728**	=.1192	**=.0442**	**=.0286**	=.8026	**=.0023**	**=.0333**	=.3081	=.5747	**=.0006**	=.0995	**=.0023**	**=.0834**	=.7355	=.5281	=.3395	**=.0553**	=.3582	> .0001			
CORR	$PostQ_t$	**.222**	**.224**	**.168**	-.086	**.204**	**.235**	.040	**.244**	**.235**	-.020	-.023	**.3246**	.149	**.247**	**.172**	.149	-.107	**-.174**	**.199**	.139	**.954**	**.834**	1	
Prob		**$p = .015$**	**=.0137**	**=.0667**	=.3482	**=.0254**	**=.0097**	=.6646	**=.0072**	**=.0097**	=.8257	=.802	**=.0003**	=.1048	**=.0064**	**=.0598**	=.1035	=.2457	**=.0569**	**=.0295**	=.1376	> .0001	> .0001		
CORR	**Dur**	.043	.100	-.030	**-.147**	**.152**	**.175**	.029	**.185**	**.189**	-.005	-.009	**.1926**	.135	**.160**	.044	.069	.015	-.066	.148	-.032	**.578**	**.563**	**.544**	1
Prob		$p = .6408$	=.2793	=.7447	=.1097	**=.0965**	**=.0555**	=.7498	**=.0432**	**=.0389**	=.9595	=.921	**=.0351**	=.1407	**=.0812**	=.635	=.4543	=.8723	=.4732	=.1078	=.7313	> .0001	> .0001	> .0001	

Note: **Stat** = Statistic; **Var** = Variable; **CK** = Computational Knowledge; **Pre** = Prior Computational Knowledge; **Post** = Subsequent Computational Knowledge; Δ_{CK} = Difference between Prior and Subsequent Computational Knowledge; Enj_1 = Enjoyment before Treatment; Enj_2 = Enjoyment after Treatment; Δ_{Enj} = Difference in Enjoyment before and after Treatment; Exc_1 = Excitement before Treatment; Exc_2 = Excitement after Treatment; Δ_{Exc} = Difference in Excitement before and after Treatment; M_E, M_U, M_S, M_I = Motivational Factors of Empowerment, Usefulness, Success, and Interest respectively; T_A, T_C, T_E, T_N, T_O = Personality ; **Age** = Subject's Age; Q_t = Duration of answering both CK Quizzes; $PreQ_t$ = Duration of answering CK Quiz before Treatment; $PostQ_t$ = Duration of answering CK Quiz after Treatment; **Dur** = Study Session Duration.

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