SCIENTIFIC REALISM AND FINAL CAUSES: A NEW METHOD FOR VISUALIZING FINAL CAUSES IN ICONIC MODELS

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Abstract:
In light of documented methodological issues and reproducibility failures, psychologists have sought to improve the scientific credibility of their field. Unfortunately, these efforts have not addressed psychology's problematic foundational philosophy, logical positivism, which has largely been abandoned by modern philosophers. Notably, other older sciences such as chemistry and physics have also replaced logical positivism with a stronger foundation, namely, philosophical realism. This thesis demonstrates how psychologists can overcome their methodological issues and reproducibility failures by likewise embracing a realist philosophy of science that includes Aristotle's four cases (viz., the material, formal, efficient, and final causes). Final causes are particularly important as they explain the purpose or reason for the occurrence of an event in nature. Utilizing Perceptual Control Theory, this thesis provides a general methodology for visually representing such causes in iconic models. Perceptual Control Theory posits that organisms are aware of sensations in the environment and respond to the awareness of these sensations towards some goal (i.e., final cause). In other words, behavior is a result of a goal held by the organism and is not merely produced from the environment. Data from a perceptual control theory task were collected and analyzed to determine the number of individuals whose responses matched the proposed final cause model. Results were highly successful as every individual's set of responses could be traced accurately through the model. Further implications and the importance of these modeling procedures are discussed. Utilizing the modeling technique developed in this thesis, psychologists can begin to rebuild their research upon the foundation of philosophical realism. In doing so, psychologists will be enabled to produce fruitful research which also restores the individual person to the center of investigation, offers inferences to best explanations, improves model testing and theory development, and most importantly, restores teleological explanations to psychological science.

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CHAPTER I

INTRODUCTION

Arocha (2020) recently discussed that psychologists have addressed psychology's statistical and methodological shortcomings without emphasis upon its philosophical foundation. Particularly, the philosophical foundation of psychology has produced five assumptions: the input-output (I – O) assumption, the random variable assumption, the probability assumption, the aggregate assumption, and the frame of reference assumption. These assumptions are largely responsible for the statistical and methodological concerns and must be addressed.

To address the five assumptions, Arocha (2020) argues that psychologists must abandon the psychology's current philosophical foundation (viz., positivism) and replace it with a philosophy that has withstood the test of time, realism. Realism, however, is incompatible with the five assumptions held by psychologists, particularly the I – O assumption. For a realist, the purpose of scientific inquiry is not to understand a natural system as a collection of generic inputs and resultant outputs, but rather to understand the causal structures and dynamics of the system through Aristotle's four causes (material, formal, efficient, and final). Problematically, psychologists have generally failed to distinguish between the different causes and have particularly lost sight of final causes. While a few psychological researchers have incorporated final causes in their studies, no general method for modeling and analyzing final causes has been put forth.

The current paper, therefore, provides the first general methodology to model final causes in visual models. To do this, the current paper utilizes a psychological framework, Perceptual Control Theory (PCT), because it employs the notion of final causality. Unfortunately, PCT routinely conducts data analysis similar to the standard research model of psychology, the I – O assumption. Therefore, the current paper recommends and demonstrates an alternative data analysis approach, Observation Oriented Modeling (Grice, 2011). The purpose of the current paper is therefore to address several key issues. These issues are summarized as follows,

1. Psychology is founded on an outdated and problematic philosophy, positivism.
2. The overreliance upon positivism has produced five problematic assumptions in psychology, as described above. The I – O assumption is regarded as the primary assumption within psychology's standard research model and is, therefore, the most problematic.
3. Due to the reliance on the I – O assumption and problematic philosophical foundation, psychologists have largely abandoned explanations of final causes in nature.

To resolve these issues the current paper proposes the following recommendations,

1. Psychologists should reconstruct psychology's philosophical foundation with a philosophy that explicates the structures and dynamics of nature, realism.
2. Realism is incompatible with the I – O model, therefore the current paper recommends that Aristotle's four causes be utilized in place of the standard research model of psychology.
    a. Psychologists must restore final causality as the center of scientific investigation, as such the current paper demonstrates a novel methodology to depict final causes in a model. Perceptual Control Theory (PCT) is used to demonstrate a novel methodology for depicting a final cause within a visual model.

b. Data from PCT studies are routinely analyzed in a way consistent with the I – O assumption. Consequently, the current paper demonstrates a method of data analysis that departs entirely from the I – O assumption and is consistent with the proposed final cause model.

CHAPTER II

REVIEW OF LITERATURE

Background

Arocha (2020) recently described several foundational issues that have impeded psychology's development into a mature and complete science. These issues include methodological shortcomings (see Cohen, 1994; Ioannidis, 2005; Lykken, 1991; Meehl, 1978), an overreliance upon Null Hypothesis Significance Testing (NHST; Acree, 1978; Arocha, 2020; Gigerenzer, 2004; Hubbard, 2016; Lambdin, 2012; Nickerson, 2000; Rozeboom, 1960; Wasserstein & Lazar, 2016), and reliance upon an abandoned philosophy, positivism (Arocha, 2020; Costa & Shimp, 2011; Dougherty, 2013; Grice, 2011; Manicas, 2006). Psychologists have acknowledged and attempted to address some of the methodological and statistical issues.

For example, recent work by John and colleagues (2012) discusses 10 Questionable Research Practices (QRPs) within psychological science. Concerningly, several of the QRPs are specifically related to psychology's methods and reporting, such as "failing to report all of a study's dependent measures; failing to report all of a study's conditions; and deciding whether to collect more data after looking to see whether the results were significant" (for all 10 QRPs see Table 1 in John et al., 2012, p. 525; see also Simmons et al., 2011). In addition to these concerns, the Reproducibility Project (Open Science Collaboration, 2015) reveals that psychological studies may fail to replicate at an alarmingly high rate.

In response to the methodological issues (e.g., QRPs and replication concerns), psychologists are advocating for open-reporting of all methods (see Ferguson, 2015; Kidwell et al., 2016; Shrout & Rodgers, 2018; Simmons et al., 2011), pre-registration of studies (see Davis-Kean & Ellis, 2019; Nosek et al., 2018; Wagenmakers et al., 2012), making data publicly available (Ferguson, 2015), and conducting direct replication studies (see Koole & Lakens, 2012; Nosek et al., 2018; Simmons, 2014). To address the statistical concerns, specifically with regard to NHST, psychologists are recommending that researchers increase statistical power and use confidence intervals (see Cumming & Fidler, 2009), use graphical representations of data (Fidler & Loftus, 2009), collect larger sample sizes (Sakaluk, 2016), interpret and report meaningful effect sizes (Funder & Ozer, 2019), and use alternative data analytic approaches, such as Bayesian statistics (see Etz & Vandekerckhove, 2018).

Unfortunately, these methodological and statistical changes may be inconsequential without addressing their philosophical basis. Arocha (2020) points out that, consistent with positivism, too much emphasis is still placed on collecting and analyzing data rather than on developing theory. Such an emphasis reduces theory to identifying relationships (usually linear) between variables, such as in a path model, as opposed to explicating the structures and dynamics of natural systems. If the goal of psychology is to establish itself as a rigorous and mature science, then it must adopt a foundation, similar to the other successful sciences (e.g., chemistry or physics), that goes beyond simply describing relationships to explaining effects and their causes. According to Arocha (2020), Bunge (1993; 2014), Dougherty (2013), and Wallace (1996), among others, the foundation underlying these sciences is philosophical realism.

Realism is rooted in Aristotelian philosophy. Although there are a number of schools of realism,[1] according to Wild (1948) all realists adopt three basic premises: "1) there is a world of real existence which men have not made or constructed; 2) this real existence can be known by the human mind; and 3) such knowledge is the only reliable guide to human conduct, individual and social" (p. 6). Realism primarily differs from positivism in that realism asserts that one can come to know the *nature* of a thing (e.g., the noun; see Wallace, 1996). Simply put, a *nature* (also known as an *essence*, *substance*, or *quiddity*), is simply that which makes the thing what it is. More specifically, a *nature* is what allows one to intelligibly know a thing, such as a rock, and to distinguish one thing (e.g., the rock) from another thing (e.g., a Hibiscus). This ability to know a thing's nature is what makes possible the development of causal, scientific knowledge.

Positivism's philosophical roots are found in the ideas put forth by Locke, Hume, and Kant which state that all knowledge is sense knowledge (see Dougherty, 2013, p. 58). From such a viewpoint, psychologists can never truly know the natures of things, but rather through careful observation and experimentation they can only be certain of their perceptions/sense awareness of things. Wallace (1996) concludes such an understanding of scientific knowledge to be *superficies* (Latin for surface), in other words, superficial. Positivism only provides a surface view of nature and cannot provide a complete understanding of things, whereas realism maintains that all things exist independently of our perceptions or awareness of them and that one can come to know nature through investigating its causes and effects (see also Wallace, 1996).

Arocha (2020) discusses five key assumptions within psychological science's standard research model which are incompatible with realism: the input-output (I – O) assumption, the random variable assumption, the probability assumption, the aggregate assumption, and the frame of reference assumption (see pp. 5–10). The I – O assumption can be regarded as the center around which the other four assumptions revolve given that it pertains to how psychologists develop their theories. It specifically states that behavior, as selected by an observer (e.g., the researcher), is initiated by some external stimuli in the environment. Meaning the researcher notices some behavior after some external (i.e., within the environment) event. The environmental event (i.e., input), moreover, is presumed to be directly responsible for the behavioral response (i.e., output) that follows it.

As an example, imagine a psychologist who applies the I – O assumption while observing a toddler throwing a tantrum. The psychologist may speculate that the toddler's tantrum (e.g., behavioral response; output) is directly resultant from the parent's removal of a beloved toy or desired object (e.g., environmental inputs). In applying the I – O model, the psychologist is not necessarily seeking to explain a causal connection between some event (e.g., the child's tantrum) and an environmental input (e.g., the toy being taken away). Instead, the psychologist is ultimately concerned with empirically connecting the input with the output on a consistent basis. Unfortunately, such a viewpoint is irreconcilable within realism. For a realist, the purpose in scientific inquiry is not to understand the generic inputs and resultant outputs, rather, the purpose is to study and identify the causal structures and dynamics of a natural system (see Arocha, 2020; Dougherty, 2013; Manicas, 2006).

As another example and to expand upon the example provided by Arocha (2020), imagine a chemist who devotes his or her entire life to studying chemical reactions without applying any knowledge of molecular structure of the elements involved in the reaction. More specifically, suppose this chemist utilizes the traditional I – O assumption to study rust forming on iron. The chemist may start by observing rust in the real world and determining that it is 'odd' or 'peculiar' and may proceed to study several different materials (e.g., iron & copper) to determine if rust is found on several different objects or only on select objects. Once the chemist has observed rust forming on materials made with iron, the chemist proceeds to deduce a hypothesis that water droplets (i.e., the input) are what cause the rust to form (i.e., the output). The chemist may even create an experiment by placing water droplets on some pieces of iron (e.g., an experimental condition) and not placing droplets on other pieces of iron (e.g., a control condition). Based upon such an experiment, the chemist may deduce that rust only forms upon the iron-object which received the water droplet, and through the application of the I – O model the chemist would likely conclude, albeit incorrectly, that the rust occurred solely because of the water droplets. Unfortunately, and as we understand today, this is not the case as rust forms through the process of oxidization, which was only understood by studying the structures and processes (i.e., the dynamics) of the chemical compounds involved (e.g., iron, water, and oxygen).

The application of the I – O model restricts the complete understanding of a natural system by limiting the focus upon some input and its suspected output, as opposed to focusing upon the operating mechanisms. As Arocha (2020) proposes, psychologists must eschew the traditional exploration of I – O relationships and adopt a realist view that seeks explanations of causes and their effects. Specifically, realists adopt a view of causality that returns *Scientia* (Science) to investigating and modeling the causal processes and structures of natural systems through Aristotle's four causes (see Ackrill, 1988; Arocha, 2020; Grice, 2011; Falcon, 2019; Wallace, 1996).

The Four Causes of Nature

Scientia naturalis or *epistimēmē,* according to Aristotelian philosophy, is the knowledge of nature through its causes. Unfortunately, psychologists, social scientists, and even some biologists have widely conceptualized science as probabilistic[2] and have either abandoned or forgotten Aristotle's view of *Scientia naturalis*. This departure from Aristotelian philosophy has brought about an overreliance upon Comte's positivism, Pearson-Fisher's NHST, and Karl Popper's falsification and probabilistic view of science (see Arocha, 2020; Dougherty, 2013; Harré, 1970; Grice, 2011; Wallace, 1996). Philosophers and scientists alike, however, have critiqued the 'Popperian' method of science by articulating issues with deductivism and falsification.[3] More importantly, many of these scholars have advocated for the return of Aristotle's four causes as the foundation for scientific investigation (e.g., Arocha, 2020; Dougherty, 2013; Grice; 2011; Harré, 1970; Manicas, 2006; Rychlak, 1988; Wallace, 1996).

The first detailed accounts of Aristotle's four causes appear within his *Physics* (Book II, Chapter 3) and *Metaphysics* (Books I –VII; particularly Book V, Chapter 2) and are labeled as *material*, *formal*, *efficient*, and *final* causes.[4] Within *Physics II* Aristotle states that things have natures and that these natures can be best understood through the four causes. Aristotle begins with the most basic of the causes, *material causes*, which are defined as the matter (from the Greek *hulê*) that comprises the thing (see Falcon, 2019; *Metaph.* V.2, 1013a 24 –1014a 25; *Phys.* II.3, 195a 16–35). The second cause discussed by Aristotle are *formal causes*. Formal causes are simply the form (i.e., shape or pattern) of the thing, and "what it [the thing] is to be" (see *Metaph.* V.2, 1013a 24 – 1013b; *Phys.* II.3, 195a 16 – 35). Formal causes can be differentiated between two 'types' referred to as *substantial forms* and *accidental forms*.

According to Aristotle the substantial form is that which is essential to make the thing what it is, whereas accidental forms are non-essential properties of a thing that do not substantially change what the thing is (see Ainsworth, 2020; *Metaph.* V.2, 1013b 30 – 1014a 25; *Phys*. I.7, *Phys.* II.3, 195a 16 – 35). Simply put, the substantial form allows you to know what the thing is, whereas accidental forms allow you to differentiate between two of the same things. For example, suppose one is concerned with the forms of bonsai trees. The substantial form of the bonsai tree are its general features, such as its organic nature, specific biological composition, and the characteristics held by all bonsai trees that are essential to bonsai trees. The accidental form would be the specific differences between one bonsai tree and another. For example, a pruned or shaped bonsai tree would possess an accidental form that is different from a bonsai tree that has been left unpruned or unshaped. In this specific instance, the accidental forms differ in that one bonsai tree is pruned and shaped to a specific liking and one is not. Through understanding the substantial form of a bonsai tree, however, one knows that both the pruned and un-pruned bonsai trees are in fact bonsai trees, despite their differences in accidental properties.

The third of the four causes are *efficient causes*, which Aristotle defines as that which initiates the generation or change of the thing. In other words, efficient causes are the process by which the thing comes to be or changes over time. The last of Aristotle's four causes, and the most important, are *final causes*. The final cause, according to Aristotle, is the end, the goal, the purpose, or more explicitly "that for the sake of which a thing is done" (see Falcon, 2019;

Metaph. V.2 1013a 30 – 35). Simply put, the final cause is the answer to the 'why' question one might ask regarding a thing or natural system (e.g., why did the iron rust?).

As an example for understanding Aristotle's four causes, consider a wooden stool. The material cause of the wooden stool is that which makes up the 'thing.' In other words, the *material cause* of the stool is the wood itself, understanding that stools can also be made of an entirely different material, such as metal. The *formal cause* of the stool is the physical manifestation of the wood in a particular shape or form. In this case let us imagine it is a stool with four legs and a round, flat, base to sit on without any back support. The general 'stool-like' features would be considered its *substantial form*, whereas the color of wood would be considered its *accidental form* – the stool can be colored with various stains without changing what it is (i.e., a wooden stool). Similarly, the number of legs the stool possesses is also an *accidental form* since it could also be constructed with four legs rather than three. The quantity of legs may change one stool's specific shape compared to another, but it would not substantially change what the thing is (e.g., an instrument to be sat on without back support).

The stool (i.e., the formal cause) has already been established to be made up of wood (i.e., the material cause) and fashioned into a particular shape, but how and to what end? To answer these two questions, one must turn to the efficient and final causes. Through the understanding of *efficient causes*, one can grasp the process by which the material reaches the desired form[5] (i.e., how it was constructed or came to be). The *final cause* is why the stool was crafted in the first place. In this instance, suppose it was because the carpenter was trying to make a living. The ultimate reason the stool came to be, then, is because the carpenter wanted to make money. More generally, according to Aristotle, a complete explanation of a thing or natural system under investigation can only be achieved when one considers its final cause.

The final cause, then, is the most important cause as it provides the explanation for why the material, formal, and efficient causes are operating (*Metaph*. V.2, 1013a 30–35; see also *Phys*. II.3, 194b 30–35). While the latter three causes are important, without consideration of the purpose (i.e., why something occurs), the knowledge gathered from these causes is incomplete (see also Falcon 2019; O'Donnell, 1995; Wallace, 1996). Importantly, Aristotle argued that final causes exist in most things, and do not occur purely as human 'purpose' or 'intent;' meaning, final causes can be found in all of nature, such as natural end states (e.g., the development of an acorn into a mature tree), homeostatic equilibria (e.g., body temperature), and natural cycles (e.g., the Citric Acid cycle). As a more detailed example, Wallace (1996) summarizes William Harvey's anatomical classic, *On the Motion of the Heart and Blood in Animals*, by stating,

> "His [William Harvey's] final chapter servers as a summary and synthetic exposition of the definition of the heart, touching on all four of its causes, namely: its formal causes, the anatomical structure described in terms of its function; its material cause, the muscular and other tissue sustaining this structure and operation; its final cause, the circulation of the blood; and the efficient cause of the circulation, the contraction whereby the heart fulfills its function." (p. 353)

Harvey relied upon Aristotelian philosophy to explain why blood circulates through the body as it does. The final cause, the circulation of the blood, is here seen as an 'end' that fulfills a function and is not regarded as an intention or goal. Human intent and purposes are far easier to identify as final causes than the same types of causes in natural systems, however, it is important to distinguish that final causes are not always intents, purposes, or goals. In the realm of human action, it is also easy to understand Thomas Aquinas' view of final cause as both the end as well as the beginning, and it is only through the final cause that causality is possible (as cited by O'Donnell, 1995). Aquinas regarded the final cause as both the first cause operating in nature in addition to the last cause. As stated by O'Donnell (1995),

> "Although it may sound like contradistinction in terms, we can say that the *final* cause is the *first* of all causes, because without the final cause there would be no causality whatsoever … the final cause is the motivation, the purpose, the goal, the end, which the efficient cause has in mind before it begins to act, before it exercises its causality. That is

why we can call it the *first* cause. But we can also call it the *last* cause, since it is the goal which is accomplished only after the efficient cause produces the effect." (p. 16)

Returning to the example of a carpenter constructing a stool, the material cause is the wood, the shape or pattern of the stool is the formal cause, and the process by which the stool comes together represents the efficient causes. The final cause, or the purpose, of the stool being crafted may be one of several, as it again depends upon the individual carpenter. What is important, however, is that the final cause explains the entire process, in other words, why the carpenter crafted the stool. For example, through understanding the final cause, one can understand why the carpenter may have chosen oak wood instead of pine as the material for his stool. The carpenter may have reasoned that oak is sturdier than pine, and ultimately the carpenter's goal was to craft a sturdy stool. Thus, the purpose or reason (i.e., the final cause) for crafting a sturdy stool, influences the materials that the carpenter selects.

The final cause, moreover, initiates the change of the material into the desired form. Without the final cause, there is no purpose within nature, meaning that the choice of the type of wood would be arbitrary (i.e., random) to all but the chooser. Without understanding 'why' the stool is being crafted, one cannot understand the integrated whole of the material, formal, and efficient causes. Instead, one would know these causes as they appear, without any additional explanation. For instance, one can know that the material chosen was oak wood over pine wood, but one would not know why one material was chosen over the other. Concerningly, this might even leave one speculating that such a choice was entirely random or nonsensical (see the Random Variable Assumption in Arocha, 2020, pp. 5 – 6). Finally, a complete understanding of the stool itself must entail its purpose; it is an object to be sat upon or stood upon, rather than an object to be used for some other purpose (e.g., to shelve books).

Unfortunately, within psychology and other social sciences (e.g., anthropology, health science, etc.) Aristotle's idea of final causes has been predominantly abandoned[6] (see Arocha, 2020; Dougherty, 2013; Manicas, 2006; Rychlak, 1988). The rejection of a teleological view of nature, in other words the failure to consider final causes, is problematic because it leaves scientists with an incomplete and entirely mechanistic view of nature and causation (see Arocha, 2020; Dougherty, 2013; Grice, 2011; Manicas, 2006; Rychlak, 1988). As Dougherty (2013) states,

> "An explanation in terms of a final cause is an attempt to render an action intelligible by giving its end or purpose, the reason the activity takes place. To deny the principle of finality is to deny that change is intelligible. Just as man's activity is unintelligible apart from its purpose, so too is all activity in nature unintelligible apart from its purpose. An explanation solely in terms of efficient cause is not satisfying." (p. 63)

Dougherty's final statement can be rewritten as follows, "an explanation solely in terms of [inputs and their generic outputs] is not satisfying." As demonstrated in the chemistry example above, a true understanding of nature cannot be found solely through generic inputs and their corresponding outputs. Rather, a more complete understanding of nature (i.e., scientific knowledge) only occurs when one understands for the sake of which an event occurs (i.e., final causes). Fortunately, not all psychologists have abandoned the investigation or inclusion of final causes within psychology.

By developing and testing his Logical Learning Theory, Rychlak (1988) has shown that final causes can be taken seriously in psychological research. Specifically, Rychlak (1988) distinguished that behavioral responses are final causes and that researchers studying behavioral responses in humans are in fact interested in final causes. Rychlak (1988) coined a new term to include final causes within his Logical Learning Theory, which he named *telosponse*. Rychlak (1988) reasoned that a *telosponse* occurs when a person takes on some meaningful item and acts upon it as the sole purpose for which a behavioral response occurs. Meaning, an individual is *telosponding* when the individual behaves for the sake of some purpose or intention. For example, the carpenter is *telosponding* when he crafts the stool for the sake of making an item to sit upon.

Final causes remained the centerpiece of Rychlak's (1988) investigations across 20 years of developing his Logical Learning Theory.

More recently, Grice and colleagues have demonstrated how final causes can be incorporated in psychological studies on in-group/out-group biasing (Grice, 2011, Chapter 7), interpersonal judgments (Grice, 2015), Terror Management Theory (Grice et al., 2012), and memory (Grice et al., 2017). The methods of modeling final causes across these various studies, however, have not been uniform. Rychlak (1988) also failed to provide a general set of tools for modeling final causes. What is needed, then, is a general methodology for visualizing final causes, which will further initiate the departure from I – O models and their accompanying assumptions. As Arocha (2020) demonstrates, Perceptual Control Theory is a viable contemporary theory in psychology which similarly interprets and recognizes the importance of final causes. As such, it can serve as an excellent starting point for developing and explicating a novel and general method for modeling final causes.

Perceptual Control Theory

Through his Perceptual Control Theory (PCT), William T. Powers (1973, 1978) postulates that behaviors are a direct result of controllable perceptions. In other words, an organism cannot directly control its behavior or environmental conditions, however, the organism can control its perceptions. Powers' (1978) demonstrates this notion through a simple computer task in which a person is instructed to maintain a cursor position in reference to a grid of stationary dots. The person, however, cannot control the external disturbances, which are programmed into the computer to move the cursor randomly either up or down. Rather, the person is only able to control his or her perceptions of the cursor's position on the cathode-ray tube (CRT) display; specifically, whether the cursor is aligned or misaligned with the target as instructed. Powers (1978) demonstrated that persons completing this task elicited behavioral responses consistent with their perceptual awareness of the cursor. For instance, if the computer program moved the cursor up, the participant perceived the change and responded by pulling the cursor back down to the target location.

Richard S. Marken (2014) created the Nature of Control Task to be a computerized PCT task analogous to the task first developed and utilized by Powers (1978). Figure 1 presents an image of what the task looks like. The task is rather straightforward as the participant's goal is to keep the mouse (i.e., the cursor) aligned with the target, which in this case is the vertical black line in the center of the screen. The goal therefore equates to keeping the Error (E) equal to zero (or close thereto), which would indicate that the cursor (C) is in perfect alignment with the target. This goal can be mathematically represented as $E = T - C = 0$. Unbeknownst to the participant, however, disturbances are pre-programmed within the task to push the cursor either to the left or to the right with varying forces. For example, when the participant clicks go to begin the task, the cursor may be aligned with the target but may slowly fade to the left. The participant would then have to counteract this disturbance by dragging the cursor to the opposite side, in this case toward the right with varying force so as to restore the cursor's alignment with the target. As shown in Figure 2, Arocha (2020, p. 12) provides a visual model of the causes and effects underlying this Nature of Control task.

The reference signal (r) in the model is received (i.e., perceived) from higher control units in the nervous system (e.g., Occipital lobe), and it refers to the object to which the participant directs his or her perception toward. Better put, it is some want, intention, perceptual end state, or a goal (see Arocha, 2020; Powers, 1978, p. 419). The reference signal (r) appears in this specific model as the goal, which is to keep the cursor aligned with the target.

The comparator (c) is the process of the person's perceptual awareness of the reference signal compared against the goal. In this case, it is simply the perceived current position of the cursor in relation to the target, in addition to, a judgement of whether the cursor and target are aligned or misaligned. When the perception of the cursor position matches that of the target (i.e., reference signal), the person, often referred to as the control system in PCT research (see Arocha, 2020), does nothing in response. When the perception of the cursor position (i.e., the input signal) does not match the target (i.e., the reference signal), an error is computed.

The error is the mathematical difference between the cursor position and the target location (E = T – C). The error, however, is not actually 'seen' by the participant, but rather it is perceived through the comparison process. For example, the person perceives that the cursor position does not matchup with the target location, though the person does not see the mathematical computation of the error. If there is any error between the position of the cursor and the target, then the person must behave to counteract these effects. Error is typically brought about by and perceived through environmental disturbances (d), which in this case impact the person's ability to reach the goal.

The disturbances (d) in the current model appear as environmental 'noise' that creates a misalignment between the cursor position and the target location. Unknowingly to the participant, disturbances are pre-programmed into the task and will automatically cause the current cursor position to drift away from the target location. The participant, therefore, behaves in a manner to counteract these perceived disturbances, and ultimately attempts to remove any error between the cursor's position and the target. Participants, moreover, do not actually 'see' the disturbances but become perceptually aware of them when the current cursor position is misaligned with the target. In other words, the person perceives that disturbances are occurring when there is some error between the cursor's position and the target location. The disturbance, then, is ultimately what creates the error between the cursor's location and the target position. In addition, participants can contribute to the disturbances as well, for example, a quick jerk of the mouse or a slip of the hand that increases the distance between the cursor and the target (i.e., creates more error).

Entirely antithetical to PCT, the traditional Input – Output (I – O) model assumes a mechanistic interpretation that some input, typically from the external environment and often referred to as the independent variable, is acting upon the person. In turn, these supposed 'inputs' initiate some corresponding output or behavior, often referred to as the dependent variable. PCT, in contrast to the I – O model, assumes that the input (i.e., the independent variable) appears in the form of a disturbance or hindrance to the participant, which subsequently impedes the individual's perceptual control over the behavior (i.e., the dependent variable; see Kennaway, 2020; Marken, 1997, 2009; Marken & Horth, 2011; Powers, 1978).

For a PCT researcher, the change in the DV, after the appearance of the IV, is a result of the perceptual awareness and control of the individual, rather than being 'caused' by the IV itself, as seen in the traditional I – O model. Perhaps more importantly, by understanding and emphasizing the person's capabilities to control perceptions and inevitably behaviors, the researcher is able to understand the participant's behavior. The relationship between the IV and DV is synonymous, as one is influencing the other it is simultaneously being influenced by the other. In other words, as the input affects the outputs, the outputs are subsequently affecting the inputs (see Marken & Horth, 2011). Importantly, the PCT model recognizes that the behavioral response only occurs in relation to the purpose or intentions (i.e, final causes) of the participant. In contrast, the traditional I – O model assumes that the independent variable has created some change in the environment, as reflected by the change in the dependent variable, and does not consider any notion of final causality.

PCT models are certainly more compelling compared to I – O models or other variable based models (e.g., mediation; path models, etc.). The models themselves, however, appear entirely mechanistic in construction and are akin to schematic diagrams or circuit models. Problematically, these models may not be intuitive, easily interpretable, or humanistic in appearance (see Forssell & Powers, 2009). The mechanistic style of the models is unsurprising given Powers' background in engineering. In fact, Powers' models are predominantly based upon traditional engineering control system schematics, for example Wiener's (1948) control system diagram. The 'humanistic' appearance of the models themselves could therefore be improved upon.

Another laudable feature within PCT models is that they inherently acknowledge and attempt to provide a representation of final causes; however, it is important to note that the representation of final causes could be improved upon as well. In the typical PCT model (as demonstrated previously in Figure 2), the final cause is equivalent to the reference signal. As a reminder, the final cause is that which initiates the thing or the purpose for which a thing occurs. The reference signal specifically refers to some purpose, goal, or desire perceived by the control agent. What is problematic with this representation in Figure 2 is that the final cause is not completely represented throughout the model as that which makes the thing occur.

In the basic and standard PCT models, the reference signal appears at the beginning of the model as some intention, desire, or goal, moreover, the control system continually ‘compares’ the current cursor position against the referent (e.g., Powers, 1978; Marken, 2009; Marken & Horth, 2011; Arocha, 2020). Unfortunately, this representation of final cause falls short as it is likely to be misconstrued as just another efficient cause or event sequenced in time within the experiment. The true meaning of the final cause, from a realist perspective, is indeed the intention, purpose, or goal, but it is deeper than that as it essentially holds the entire process together. The integrated whole of the final cause is crucial to represent. The final cause is both the ‘why’ or driving force that enacts all of the processes involved in producing the ‘end goal’, as well as being the actual achievement of the end goal.

Integrated Modeling and Perceptual Control Theory

One avenue for humanizing the PCT model shown in Figure 2 is by reimagining it as an *integrated model* (Grice, 2011). Such a reframing will also provide the means for representing the final cause in the PCT task more clearly and accurately. Integrated models use pictures and icons to symbolize the structures and processes of the natural system under investigation (see Harré, 1970). More importantly, they provide the means for visually representing Aristotle’s four causes as they are hypothesized to operate in nature; meaning, the models themselves identify the formal, material, efficient, and final causes as explicated in Aristotle's *Physics* (Book II, Chapter 3) and *Metaphysics* (Books I – VII; see the four causes section above; see also Wallace 1996). Compared to PCT models, integrated models are less visually mechanistic (i.e., not circuit-based models) and are more 'humanized.' Figure 3 shows the PCT task represented in Figures 1 and 2 as an integrated model.

Working through the model systematically, imagine a person, Mark, who has come to participate in the current study. The experimenter seats Mark in front of a computer screen and informs him about the goal/purpose of the study (i.e., the final cause). As can be seen in Figure 3, this appears above 'Time Point 1,' represented with the callout bubble encompassing the final cause plaque with the mathematical goal (E = T – C = 0). This symbolically represents the experimenter instructing Mark that the purpose of the study (i.e., the final cause) is to keep the cursor aligned with the target with no error, meaning, no spatial difference between the target and the cursor (E = T – C = 0). Subsequently, one can see Mark himself with the thought bubble above him, which encompasses the computer task, the pentagon, and the final cause plaque. After hearing the goal of the study, Mark must first think about and comprehend the purpose of the study.

This process is depicted by the thought bubble encompassing the final cause plaque and computer icon, which represents that the processes within the thought bubble are occurring within Mark's mind. Mark will then make a complex judgement, which is depicted by the pentagon, to compare whether the cursor is aligned or misaligned with the target, which is depicted by the final cause plaque being encompassed within the pentagon. The reason that the final cause plaque appears within this thought bubble is because the final cause first appears as an intention. Simply put, the final cause in this instance only exists within Mark's mind, as it has not yet been achieved. This representation is critical as Mark must be aware of the goal and actively understand the goal otherwise the final cause would not be enacted within the process.

The entirety of this portion of the model remains identical to the PCT model with some slight visual modifications. Instead of the reference signal being used, a symbolic representation of the final cause is utilized and represented as occurring within Mark's mind. Moreover, the comparator is not seen nor used, as this process appears within the thought bubble and is represented by the pentagon encapsulating the computer task. As a reminder the comparator is the process by which the participant determines if the target is aligned to the goal. In this case it is whether the cursor is aligned with the target in the computer task. The integrated model offers a far more compelling and humanized representation by depicting the participant and representing that these processes are occurring within the participant's mind. Contrastingly, as seen in the PCT model (see Figure 2) it is unclear without a description where these processes are occurring (e.g., in Mark's mind). Most importantly within the integrated model and unlike the PCT model, the final cause is clearly depicted throughout the model as both an intention, as seen in timepoint 1 and as being enacted, as seen in time point 3.

Continuing in the model, Mark proceeds to timepoint 2, where he would click the 'go' button on the screen to begin the task. Once the task has begun, Mark immediately enters timepoint 3. The first image in timepoint 3 represents Mark's initial cognitive (i.e., perceptual) judgement of the cursors current location after selecting go. Again, this is represented with a thought bubble encapsulating the pentagon and computerized task as the researcher cannot see Mark making this judgement, however, such a judgement must be made to achieve the goal.

After Mark determines and judges whether the cursor is aligned with the target he responds accordingly. For example, if the cursor is aligned, he responds by doing nothing, whereas if the cursor is not aligned, he would respond by moving the cursor into alignment. Once Mark has finished judging whether the cursor and target are aligned, the next part of the model comes into play, namely the disturbances. It is important to note that there is no length of time that occurs before the disturbances appear. The disturbances are programmed to occur as soon as Mark clicks go. Specifically, the task automatically starts with the cursor located below the task at the ‘go’ button, thus Mark must first bring the cursor up to the target window to gain control over the cursor line.

Suppose Mark were to accidentally jerk the mouse left or right immediately after starting the task. This ‘jerk’ would be considered a disturbance, which Mark would then counteract after perceiving that the cursor is not aligned to the target. Once the disturbance occurs, whether by Mark’s error or due to the programmed disturbance, the computer randomly moves the cursor left or right with different forces (e.g., slow to quick). Mark would then make another cognitive judgment and determine that the cursor and target are no longer aligned, namely, $E = T - C \neq 0$.

Mark, according to the final cause, would then move the mouse in such a way to counteract the disturbances. For example, if the cursor has drifted to the right, Mark would counteract the cursor by moving it to the left with enough force to counteract the disturbance while restoring the cursor to alignment with the target. This is represented in the model after the event – the square with the word ‘disturbance’ in the center. As one can see in the model, Mark perceives the change in the cursor position, judges that the cursor and target are misaligned, and then must counteract the disturbance by moving the cursor in the opposite direction. Ultimately, the final cause, keeping the cursor aligned to the target, must be maintained throughout the duration of the task (i.e., 32 seconds). If at any time the cursor becomes misaligned to the target, Mark (the participant) must move to counteract the disturbances (whether pre-programmed or due to human error). This process perpetually occurs, hence the loop portion of the model, until the task ends (i.e., after 32 seconds).

Most importantly with the representation of the feedback loop portion of the model is that the final cause plaque supersedes all the processes internalized within it (i.e., the loop portion of the model). As a reminder, the final cause is that which integrates everything or the sake of which a thing is done. The final cause plaque surrounding the feedback loop is meant to represent that everything occurring within this loop process is ultimately occurring because of the final cause (i.e., the purpose); meaning, once Mark presses go to begin the study, he enacts the final cause which is to keep the cursor aligned to the target as closely as possible.

The final cause is why Mark continues to judge whether the cursor and target are aligned, and to counteract the disturbances when the target and cursor are misaligned, for the duration of the task. Unlike the PCT model, the integrated model utilizes a clear visual representation for the appearance of the final cause as both an intention and as the cause that binds every process occurring within the feedback loop together. Comparatively in the PCT model (see Figure 2), this distinct modeling of the final cause is not found. The PCT model only includes the initial intention, but the enactment of the final cause throughout the model is absent. Moreover, integrated models can represent material, formal, and efficient as well, whereas PCT models do not differentiate between the different species of cause.

Data Analysis with Integrated Models

Another limitation of modeling in Perceptual Control Theory is that data analysis is routinely conducted in a way consistent with the I – O assumption. Specifically, PCT researcher's using these computerized control tasks compute correlations between variables to provide evidence of control. The general I – O assumption, however, assumes that the inputs are directly responsible for the outputs. In this instance the I – O assumption would presume the disturbances in the cursor's position (i.e., the inputs) to be highly correlated with the participant's mouse movements (i.e., the output). Previous work, however, has shown this is the exact opposite of what occurs (Marken & Horth, 2011). The correlation between the mouse outputs and the disturbances in the cursor position was near zero, whereas the correlation between the mouse outputs and the disturbances was approximately -1 in value (see Marken & Horth, 2011; see also Kennaway, 2020).

Within the Nature of Control task, a graphical output is provided from the tracking task results. As can be seen in Figure 4, the mouse outputs correspond with the disturbances of the cursor. Marken (2014) uses Root Mean Square Error (RMSE) to compute the average deviation of the controlled item (e.g., the cursor) from the reference value. According to Marken (2014), the closer the RMSE is to 0.0, the better the individual has controlled the cursor. The computerized task also computes the correlations between the cursor and mouse movements (C – M), the mouse and disturbance (M – D), and the cursor and disturbance (C – D). As stated previously, the I – O model assumes that the C – M and C – D relationships should be the strongest, but in reality the exact opposite occurs. These two correlations are found to be the weakest, whereas the M – D correlation is found to be the strongest in absolute value (see Figure 4; see also Kennaway, 2020; Marken & Horth, 2011).

Notably, however, understanding behavior through the lens of variability and covariation begets an overreliance upon the I – O assumption (see also the Random Variable Assumption in Arocha, 2020; see Lamiell & Slaney, 2020). PCT researchers emphasize that it is not simply the inputs effecting the outputs, but that the process is reciprocal, meaning the inputs effect the outputs while the outputs also effect the inputs (see Marken & Horth, 2011; Kennaway, 2020). Unfortunately, the methods utilized to analyze data from these types of control tasks do not depart from the same methods utilized under the I – O assumption. Consequently, they hinder the PCT researcher from recognizing the centrality of final cause and from understanding how efficient causes are also operating within the control task (see Figure 3).

According to Aristotle, a final cause is enacted through efficient causes (see *Physics*, Book II, Ch. 3; *Metaphysics*, Books I – VII; see also Wallace 1996), which in this case occurs when the participant moves the mouse to counteract the disturbances in order to keep the cursor aligned with the target (i.e., in accordance with the final cause). Computing correlations between variables misses the important aspect of time in the efficient cause relationship between the cursor disturbances and mouse movements. Specifically, the cursor disturbances precede the mouse movements in time, and an analysis consistent with this causal understanding of the data should include this fact.

Observation Oriented Modeling (OOM; Grice, 2011) is an alternative method for analyzing the data from the PCT task that is rooted in the integrated model in Figure 3. That is, OOM enables the researcher to understand how the efficient causes are executed in accordance to the final cause. The person must first perceive that some disturbance is acting upon the cursor, which occurs when the individual perceives that the cursor is misaligned from the target. After perceiving the misalignment, the individual must then respond to the perceived disturbances by counteracting them and moving the mouse (i.e., mouse outputs) back towards the target line. In this specific instance, the disturbances are considered the causes and the mouse outputs are considered the effects. The steps taken by the participant counteracting the disturbances are the efficient causes, and the resultant alignment with the target (i.e., the goal) is the final cause.

Within OOM, there is an analysis, referred to as the Efficient Cause Analysis (ECA), which analyzes cause/effect relationships derived from an integrated model (see Grice et al., 2015; Grice et al., 2017). The ECA specifically analyzes the patterns of the observations in accordance with the hypothesized cause – effect relationship to determine the amount of instances in which one variable, referred to as orderings in the OOM software (see Grice, 2011), corresponds to a change in another ordering. The ECA can be utilized in the PCT task to determine the quantity of times in which the mouse outputs occurred in accord with the cursor disturbances. In other words, the ECA can be used to determine whether the changes in the mouse outputs matched the changes in the disturbances.

It is expected that the mouse outputs result because of the perceived disturbances, therefore, the ECA is utilized to determine the number of occasions in which the mouse outputs reciprocally matched the disturbances, but after the disturbance is perceived. For example, the disturbances are pre-programmed within the task using a sine wave function to randomly compute the disturbance quantities. Suppose then at one instance (e.g., 16ms of the tracking data) the disturbance value is computed to be -15, it would be expected that the quantity of the mouse output is reciprocal at +15, which would create perfect alignment (E = 0) or close thereto (e.g.,

+14 or +16). Using the ECA, the patterns of the observations are first compared to determine whether the mouse outputs came in response to the disturbances, meaning, after the disturbances (i.e., an ordinal relationship). Next the ECA considers whether the degree of the mouse output (e.g., +15) matches that of the disturbance (e.g., -15). The total quantity of instances in which the mouse outputs occur simultaneously with the disturbances is tallied and converted into a percentage, referred to as the Percent Correct Classification (PCC) index (Grice, 2011). The PCC indicates the total percentage of instances which matched expectations (Grice, 2011; Grice et al., 2020), meaning, the PCC indicates the total percentage of mouse movements that came simultaneously in response to the disturbances.

The ECA is superior to the correlation and RMS error statistics because it enables a researcher to analyze a final cause as it is executed through time-ordered efficient causes. In other words, through analyzing the efficient causes – the resultant changes in the mouse movements in response to the disturbances – one is able to track the final cause being achieved (e.g., the cursor being aligned to the target). Importantly, using the ECA in the context of the integrated model in Figure 3 not only enables one to know how the final cause is achieved (i.e., counteracting the disturbances to maintain alignment), but also why the mouse outputs are occurring (i.e., because of the final cause).

The final cause is the reason the efficient causes occur, but the efficient causes are simultaneously occurring to bring about the final cause. In order to demonstrate how the ECA can be used to analyze data from the PCT task, we will collect responses from a sample of predominantly undergraduate and graduate students located in the Southcentral United States. We expect the results to match the efficient causes in the model in Figure 3 above, such that the mouse movements will result because of the disturbances. These results will also support the final cause in Figure 3 as participants attempt to control the cursor for the sake of the goal; that is, keeping the cursor aligned to the target with little to no error.

CHAPTER III

METHODOLOGY

Participants

Twenty-four individuals participated in the current experiment. Participants were comprised of undergraduate students, graduate students, and a non-student from the local community. The undergraduate students were recruited to participate in the current study through the university's online recruitment system (SONA) and the remaining participants were recruited by word of mouth. Previous studies have utilized relatively small sample sizes, roughly 6 – 10 persons (see Powers, 1978; Marken, 1980). Therefore, the current research collected data from 12 males and 12 females who were between the ages of 18 and 35 (*M* = 22.17, *Mdn* = 20.50, *SD* = 4.37). Regarding participants' ethnicity, the majority identified themselves as Caucasian (62.50%), with the remaining participants identifying as Black/African America, bi-racial (American Indian/White), Asian, Middle Eastern, and Latino/Latina/Hispanic. Due to the small sample size and to ensure confidentiality, the percentages of individuals who identified as being non-Caucasian (e.g., Asian or Biracial) are not reported. There were no meaningful differences produced in the results across the different ethnic individuals identified within the current experiment.

Materials

The Nature of Control Task

The nature of control task (Marken, 2014) is a simple, computerized and modernized perceptual control task similar to tasks previously employed by PCT researchers (for examples see Powers, 1978; Marken, 1980). More specifically, the task shows two vertical lines on a computer screen. One line, positioned on the top, is the target and the second vertical line, which appears directly below the target, is the cursor (see Figure 1). Furthermore, disturbances have been pre-programmed into the task to push the cursor in a randomized direction (e.g., right or left) with a randomized force (e.g., slow or fast). The direction and force of the disturbances are randomly produced by way of a sine wave function programmed into the task. The goal of the task is to keep the cursor line perfectly aligned with the target line by moving the mouse to counteract any error between the cursor and the target. The whole control task lasts for approximately 32 seconds, during which the data is recorded every 16ms. Data is recorded within the console in the web browser only 1000 trial points out of 2000 possible per person are available for analysis for each run in the task. Each trial point corresponds to 16ms worth of tracking task data.

Procedure

All procedures were approved by the Institutional Review Board (Approval Code: IRB-21-245) at a local Midwestern University. During the recruitment phase, participants either signed up for a time slot through the SONA system or communicated with the first author to schedule a time to participate. After confirming their research timeslot in the laboratory, participants arrived at the scheduled time and were presented within an informed consent document. Once the participants had read and signed the informed consent, participants were presented with a questionnaire that assessed demographics such as age and biological sex. The demographics questionnaire was given in a counterbalanced fashion such that participants either completed the demographics form before completing the computer task or after completing the computer task. To maintain anonymity given the small sample size, no other demographic information was collected.

Upon completion of the counterbalanced demographic items, participants sat in front of a computer monitor approximately 15 inches but no further than 20 inches away from the screen, which was positioned directly in the center of the desk cubicle. For the experiment, the mouse was set up for a right-handed individual with a dots per inch (DPI) setting equal to 1500. DPI is a measure of how fast the cursor moves on the screen when one moves the mouse. The higher the dpi setting, the faster the cursor moves and vice versa. A Logitech G502 HERO high performance gaming mouse was utilized due to the low latency of the mouse, ability to control the dpi setting, and customizability for the weight of the mouse. The mouse had a base weight of 121g, with 3 additional 3.6g weights inserted for a total of 131.8g. The lower the mouses latency, the lower the lag is from when the mouse is moved to when the cursor is moved. A latency of 1ms means that the cursor is refreshing every millisecond, so that there is little to no apparent lag between mouse movements and cursor movements on the screen.

Participants were instructed of the task and given an opportunity to practice the task. Participants were required to complete a first run, at least one practice trial, and then two test trials. Participants were allowed to repeat the practice trials as many times as desired until the individual felt comfortable with the task. Most participants completed one practice trial (n = 17), a handful took two practice trials (n = 5), and a couple of individuals took three practice trials (n = 2) after the initial first run. There were no meaningful differences produced from the participants who chose to practice more than one additional time beyond the initial first run. Similar to the methodology of Marken (1980), participants rested for 30 seconds before completing the next trial. Participants therefore completed the first run, rested for 30 seconds, then completed at least one additional practice trial, then rested for another 30 seconds, then completed the first test trial, followed by another rest, and so forth until completing the second test trial.

Once participants were ready to start the trial, they clicked ‘new run’ on the computer and the task immediately began. The participants then controlled the mouse to counteract the programmed disturbances to keep the cursor aligned with the target. Upon completing the first and second test trial, participants who were assigned to take the demographics questionnaire after the task then completed the questionnaire. Upon completion of the demographic questionnaire (when relevant) or the test trials, all participants responded to a final prompt which read, “Using the space below please explain why you chose to move the cursor in the way that you did.” Participants were then given as much time and as many characters/words as necessary to answer the prompt. These qualitative responses (see Table 12) were then saved and are briefly considered within the discussion section. All participants were then debriefed and dismissed from the study. To maintain anonymity and to place emphasis upon the individuals, all persons were given a novel name, which were not used by any individual who participated within the current experiment.

The data produced during the practice trials was not saved and is not considered within the current results section. The data from the first run, test trial 1, and test trial 2 are used within the analyses in the results section below. Accordingly, there are 3,000 possible data points per person.

CHAPTER IV

FINDINGS

The complete results for both the OOM and traditional analyses of the disturbance and mouse (D-M), disturbance and cursor (D-C), and mouse and cursor (M-C) are first presented for 2 individuals, the ‘best’ case (Luke) and the ‘worst’ case (Ruth). The best (Luke’s test trial 2 output) and worst (Ruth’s first run output) cases were determined by the highest (best) and lowest (worst) PCC values for the D-M relationship across either the first run (FR), test trial 1 (TT1), or test trial 2 (TT2). Following the complete reporting for the best and worst cases, summary statistics are reported for all individuals. Three decimal places are utilized for the D-M correlation to show the subtle differences across each individual because the majority of the correlations equaled -.99 or -1 if rounded to two decimals.

As a reminder to the reader, the results produced by the Efficient Cause Analysis (ECA) within OOM are the primary focus; however, traditional analyses (correlations, RMSE, and stability) produced by the PCT task were also included for comparison purposes. The results should follow the expected hypotheses such that the D-M relationship will produce the highest effect (i.e., highest PCC) compared to the D-C and M-C relationships. This pattern should be observed for all individuals across all trials (FR, TT1, & TT2).

Each PCC was computed from the Efficient Cause Analysis by comparing all ordinal pairwise relationships between the two orderings of interest (e.g., Disturbance & Mouse outputs). For example, consider three timepoints, Interval 1 (I1), Interval 2 (I2), and Interval 3 (I3), for the disturbance and mouse output. If the disturbance and participant’s mouse movements both simultaneously decrease or increase from I1 to I2, then this change is counted as a correct classification. Similarly, changes in the disturbance and mouse movements are compared for I1 versus I3 and for I2 versus I3. The PCC is computed as the percentage of simultaneous changes in the disturbance and moue movements for all three time point comparisons. In the current example there would be ${}_3C_2$ comparisons, or 3 total comparisons.

Within the current experiment 1,000 total intervals were examined in this fashion, yielding a total of 499,500 (${}_{1000}C_2$) comparisons for each relationship (D-M, D-C, & M-C) across each trial (FR, TT1, & TT2). Each PCC can be directly interpreted as the percentage of 1) mouse movements that came immediately in response to (i.e., simultaneously with) the disturbance movements (D-M relationship), 2) cursor movements that came in response to (i.e., simultaneously with) the disturbance movements (D-C relationship), or 3) cursor movements that came in response to (i.e., simultaneously with) the mouse movements (M-C relationship). Given the equal quantities of comparisons (499,500 total) across all 3 trials (FR, TT1, & TT2) and all 3 relationships (D-M, D-C, & M-C), the PCC can be interpreted in the same way one would interpret a standardized effect size; meaning that the largest PCC indicates the strongest relationship for the D-M, D-C, or M-C relationships which can be directly compared across trials (FR, TT1, or TT2).

Best Case

Starting with Luke's FR output, the ECA for the D-M relationship revealed that 479,818 of the 499,500 D-M pairs matched expectation, PCC = 96.06%, *c-value* < .0001.[7] These results indicated that approximately 96% of Luke's mouse movements came directly in response to (i.e., after) the disturbances. For the D-C relationship, the ECA revealed that only 296,034 out of 499,500 D-C pairs matched the expectations, PCC = 59.27%, *c-value* < .0001. These results indicated that around 59% of Luke's cursor movements came directly in response to the disturbances. Finally for the M-C relationship, the ECA revealed that 302,613 out of 499,500 M-

C pairs matched the expectations, PCC = 60.58%, *c-value* < .0001. These results indicated that about 61% of Luke's cursor movements came in response to his mouse movements. For Luke's FR results, it is overwhelmingly clear that the PCC from the D-M relationship (~96%) is the strongest, compared with the PCCs from the D-C (~59%) and M-C (~61%) relationships.

For Luke's TT1 output, the ECA for the D-M relationship revealed that 473,118 out of 499,500 D-M pairs matched the expectations, PCC = 94.72%, *c-value* < .0001. Whereas only 296,650 out of 499,500 D-C pairs matched the expectations (PCC = 59.39%, *c-value* < .0001) and 301,163 out of 499,500 M-C pairs matched the expectations (PCC = 60.29%, *c-value* < .0001). For Luke's TT1 results we again found the same pattern as the FR results, the PCC from the D-M relationship (~95%) is the strongest, compared with the PCCs from the D-C (~59%) and M-C (~60%) relationships

Finally, for Luke's TT2 output, the ECA for the D-M relationship revealed that 482,026 out of 499,500 D-M pairs matched the expectations, PCC = 96.50%, *c-value* < .0001. Whereas only 272,232 out of 499,500 D-C pairs matched the expectations (PCC = 54.50%, *c-value* < .0001) and 278534 out of 499,500 M-C pairs matched the expectations (PCC = 55.76%, *c-value* < .0001). For Luke's TT1 results we again found the same pattern as the FR and TT1 results, the PCC from the D-M relationship (~97%) was the strongest, compared with the PCCs from the D-C (~55%) and M-C (~56%) relationships

Results for the traditional analyses for Luke's FR output revealed the D-M correlation (r = -0.995) to be the strongest compared with the D-C (r = -0.19) and M-C (r = 0.30) correlations, RMSE = 2.58, Stability = 9.91. Additionally, the results for Luke's D-M correlation for both his TT1 (r = -0.997) and TT2 (r = -0.997) were the strongest compared with both the D-C correlations from his TT1 (r = -0.32) and TT2 (r = -0.16) output and the M-C correlations from both his TT1 (r = 0.39) and TT2 (r = 0.23) output, $RMSE_{(TT1)}$ = 2.16, $Stability_{(TT1)}$ = 17.12, $RMSE_{(TT2)}$ = 1.89, $Stability_{(TT2)}$ = 18.29.

In considering Luke's response to the qualitative prompt ("*using the space below please explain why you moved the cursor the way you chose to*"), Luke said, "*I moved the cursor to counteract the automated movement. For example, when the cursor moved to the right I had to counteract it by moving it to the left which allowed the line to stay near the set line. Same thing applies for when the bottom line was forced to move to the left.*" Luke's qualitative response indicated that he understood the goal of the study. Luke stated that he counteracted the disturbances that moved to the right by moving the mouse to the left to stay near the 'set line,' which we know is the target line.

Across all runs, Luke's data demonstrated that he moved the mouse in response to the disturbances to keep the cursor and target aligned, in accordance with the integrated model (see Figure 3). Luke showed clearly that he was enacting the final cause, as he consistently counteracted the disturbances by moving the mouse to bring the cursor into alignment with the target and explicitly stated that he did so to stay near the set line (i.e., the target line) within his qualitative response. The PCC for the D-M relationship remained greater than the PCC for the D-C or M-C relationships across all 3 of his runs (FR, TT1, & TT2).

Figure 5 demonstrates the relationship between the disturbance values and mouse movements along with the cursor position for Luke's TT2 output, which was his best trial. In Figure 5 and all subsequent figures, the red line corresponds to the disturbance values, the black line corresponds to the mouse movement values, and the green line is the cursor position values. As can be seen in Figure 5, the red and black lines are closely intertwined, indicating that the magnitude of mouse outputs are similar to the magnitude of the disturbances. This is unsurprising, however, as we know that 96.50% of the mouse movements came in direct response to the disturbance values.

Worst Case

Starting with Ruth's FR output, the ECA for the D-M relationship revealed that 435,005 of the 499,500 D-M pairs matched expectation, PCC = 87.09%, *c-value* < .0001. Whereas only 273,900 of 499,500 D-C pairs matched expectation (PCC = 59.27%, *c-value* < .0001) and 302,613 of 499,500 M-C pairs matched expectation (PCC = 60.58%, *c-value* < .0001). Again, we found the same relationship in Ruth's FR as found across all 3 of Luke's runs. The PCC produced for the D-M relationship (~89%) was the greatest compared to the D-C (~59%) and M-C (~61%) PCCs.

For Ruth's TT1 output, the ECA for the D-M relationship revealed that 459,892 of the 499,500 D-M pairs matched expectation, PCC = 92.07%, *c-value* < .0001. Whereas only 299,121 of 499,500 D-C pairs matched expectation (PCC = 59.88%, *c-value* < .0001) and 306,510 of 499,500 M-C pairs matched expectation (PCC = 61.36%, *c-value* < .0001). Finally for Ruth's TT2 output, the ECA for the D-M relationship revealed that 460,029 of the 499,500 D-M pairs matched expectation, PCC = 92.10%, *c-value* < .0001. Whereas only 310,537 of 499,500 D-C pairs matched expectation (PCC = 62.17%, *c-value* < .0001) and 319,566 of 499,500 M-C pairs matched expectation (PCC = 63.98%, *c-value* < .0001).

Results for the traditional analyses for Ruth's FR output found the D-M correlation (r = -0.986) to be the strongest compared with the D-C (r = -0.25) and M-C (r = 0.41) correlations, RMSE = 5.11, Stability = 7.87. Additionally, the results for Ruth's D-M correlation for both her TT1 (r = -0.992) and TT2 (r = -0.992) were the strongest compared with both the D-C correlations from her TT1 (r = -0.40) and TT2 (r = -0.39) output and the M-C correlations from both her TT1(r = 0.52) and TT2 (r = 0.50) output, $RMSE_{(TT1)}$ = 3.17, $Stability_{(TT1)}$ = 9.79, $RMSE_{(TT2)}$ = 3.19, $Stability_{(TT2)}$ = 9.91.

In considering Ruth's response to the qualitative prompt ("using the space below please explain why you moved the cursor the way you chose to"), Ruth said, "*To try to make them align, I moved the cursor the way I did. I also noticed that the cursor would move away in a particular* *direction – slow at first and then faster – so, in order to keep it aligned I had to predict its direction and move it the other direction before it got too far and too fast*." Ruth's qualitative response indicated that she understood the goal of the study and was responding in accordance with the integrated model and proposed final cause (see Figure 3). Ruth stated outright that she moved the cursor in order to keep the lines aligned and that she had to change the direction and speed in which she moved the cursor in order to maintain the alignment.

Across all three of Ruth's runs, it is overwhelmingly clear that the PCC from the D-M relationship (PCC > ~87%) is the strongest, compared with the PCCs from the D-C (PCC < ~63%) and M-C (PCC < ~64%) relationships. Even though Ruth's FR was the 'worst' run, the D-M PCC produced from her output is still over 20% higher than either of the PCCs from the D-C or M-C relationships. Figure 6 demonstrates the relationship between the disturbance values and mouse movements along with the cursor position for the output from Ruth's worst run (FR). As can be seen in the figure, there is a larger discrepancy between the mouse movement output and disturbance output around the halfway mark, though Ruth was still able to counteract the disturbances fairly well to keep the cursor and target aligned.

Summary for all Individual's First Run Results

Across all individuals the ECA revealed the same general pattern of findings as shown for Luke and Ruth. The PCCs for the D-M relationship (*Min* = 87.09, *Max* = 96.38, *Mdn* = 93.69, *M* = 93.04, *SD* = 2.30) were impressively high and greater in magnitude than the PCCs for the D-C relationship (*Min* = 45.53, *Max* = 72.99, *Mdn* = 57.30, *M* = 57.86, *SD* = 6.48) and M-C relationship (*Min* = 48.23, *Max* = 75.16, *Mdn* = 59.93, *M* = 60.11, *SD* = 6.32). The traditional analyses also revealed the same general pattern of results as for Luke and Ruth; RMSE (*Min* = 1.43, *Max* = 11.47, *Mdn* = 2.89, *M* = 3.46, *SD* = 1.92), stability (*Min* = 2.84, *Max* = 22.94, *Mdn* = 11.57, *M* = 11.72, *SD* = 4.06), D-M correlation (*Weakest* = -0.884, *Strongest* = -0.999, *Mdn* = -0.994, *M* = -0.988, *SD* = 0.02), D-C correlation (*Weakest* = 0.18, *Strongest* = -0.69, *Mdn* = -0.22, *M* = -0.25, *SD* = .20), and M-C correlation (*Weakest* = -0.06, *Strongest* = 0.76, *Mdn* = 0.36, *M* = 0.37, *SD* = 0.18).

The summary statistics revealed that all of the individuals in the current experiment behaved as expected. All of the PCCs produced from the D-M relationship for the FR were higher than those produced from the D-C and M-C relationships. For ease of reference and comparison, the complete results for all individual's FR results can be found within Table 1.

Summary for all Individual's Test Trial 1 Results

Across all individual's TT1 results, the ECA revealed the same general pattern of findings for found in our two example individuals for the PCCs for the D-M relationship (*Min* = 91.10, *Max* = 96, *Mdn* = 94.26, *M* = 94.24, *SD* = 1.23), D-C relationship (*Min* = 46.16, *Max* = 66.94, *Mdn* = 56.50, *M* = 56.55, *SD* = 5.50), and M-C relationship (*Min* = 46.96, *Max* = 68.03, *Mdn* = 58.12, *M* = 58.33, *SD* = 5.72). The traditional analyses also revealed the same general pattern across all persons for the RMSE (*Min* = 1.31, *Max* = 3.67, *Mdn* = 2.60, *M* = 2.65, *SD* = 0.59), stability (*Min* = 8.76, *Max* = 24.48, *Mdn* = 13.93, *M* = 13.65, *SD* = 3.51), D-M correlation (*Weakest* = -0.989, *Strongest* = -0.998, *Mdn* = -0.995, *M* = -0.994, *SD* = 0.003), D-C correlation (*Weakest* = 0.15, *Strongest* = -0.51, *Mdn* = -0.21, *M* = -0.21, *SD* = 0.17), and M-C correlation (*Weakest* = -0.05, *Strongest* = 0.58, *Mdn* = 0.30, *M* = 0.31, *SD* = 0.17).

The summary statistics revealed that all of the individuals in the current experiment behaved as expected. All of the PCCs produced from the D-M relationship for TT1 were higher than those produced from the D-C and M-C relationships. For ease of reference and comparison, the complete results for all individual's TT1 results can be found within Table 2.

Summary for all Individual's Test Trial 2 Results

Across all individual's TT2 results, the ECA revealed the same general pattern of findings found in our two example individuals for the PCCs for the D-M relationship (*Min* =

89.96, *Max* = 96.50, *Mdn* = 94.48, *M* = 94.19, *SD* = 1.55), D-C relationship (*Min* = 44.48, *Max* = 64.59, *Mdn* = 54.27, *M* = 54.20, *SD* = 5.47), and M-C relationship (*Min* = 45.93, *Max* = 66.08, *Mdn* = 55.98, *M* = 56.12, *SD* = 5.59). The traditional analyses also revealed the same general pattern across all persons for the RMSE (*Min* = 1.39, *Max* = 4.79, *Mdn* = 2.31, *M* = 2.63, *SD* = 0.81), stability (*Min* = 8.13, *Max* = 23.73, *Mdn* = 13.91, *M* = 13.69, *SD* = 3.74), D-M correlation (*Weakest* = -0.986, *Strongest* = -0.998, *Mdn* = -0.995, *M* = -0.994, *SD* = 0.003), D-C correlation (*Weakest* = 0.14, *Strongest* = -0.44, *Mdn* = -0.17, *M* = -0.15, *SD* = .18), and M-C correlation (*Weakest* = -0.05, *Strongest* = 0.53, *Mdn* = 0.24, *M* = 0.25, *SD* = 0.19).

The summary statistics revealed that all of the individuals in the current experiment behaved as expected. All of the PCCs produced from the D-M relationship for TT2 were higher than those produced from the D-C and M-C relationships. For ease of reference and comparison, the complete results for all individual's TT2 results can be found within Table 3. Similarly, person-centered descriptive statistics, for each individual across all three runs for the ECA results and traditional results, can be found within Tables 4 – 11.

Summary of the Qualitative Items

The qualitative items for all individuals were evaluated by two raters, the first author and an independent rater. Both raters followed the same guidelines, a "0" was given to nonsensical responses that did not relate to the question or task, a "1" was given if the participants stated that they moved the cursor to the right when the disturbances moved to the left, but did not state why (i.e., they did not state they moved the cursor to maintain alignment with the target; the final cause), and a "2" was given if they stated that they moved the mouse in order to maintain alignment with the target (i.e., the final cause) or if they stated that they were at least attempting to maintain alignment (e.g., I moved the cursor towards the target line to stay lined up). Both raters agreed on 21/24 items and the 3 disagreements were then settled through a discussion.

Overall, the slight majority (*n* = 13) indicated that they were moving the cursor in order to achieve the final cause and were given a "2." The remaining individuals (*n* = 11) clearly understood that they were counteracting the disturbances by moving in the opposite direction (i.e., the efficient cause) but did not state the final cause outright, so they were given a "1." No qualitative responses were given a score of "0." Each individual's qualitative response can be read in Table 12.

CHAPTER V

CONCLUSION

The current paper echoed Arocha's (2020) argument, by analogously proposing that psychologists abandon reliance upon a positivistic philosophy and the accompanying standard research model and instead utilize a philosophy (Realism) and methodologies (Integrated Models and person-centered analyses) that advance our understanding of the structures and dynamics of psychological processes. The current paper, therefore, utilized Grice's (2011) integrated modeling technique to build and test a model based upon Powers' (1973) Perceptual Control Theory (PCT).

The PCT task examined in this study was rather straightforward as participants were instructed to control a computer mouse and keep two lines on a screen aligned. One line (the cursor line) was controlled by moving the mouse and the other line (the target) was stationary. PCT asserts that the organism controls its perceptions of events (which are received through the senses) and responds to its perceptions based upon some goal (i.e., final cause, see Powers 1973). The integrated model that was created for the PCT task was presented in Figure 3 above. As illustrated in the figure, if participants were controlling their perceptions of events, and responding (i.e., behaving) in accordance with those perceptions towards some goal (i.e., a final cause), then it was expected that the individuals would move the mouse in response to the disturbances to keep the cursor and target aligned. By comparison, the relationships between the mouse and cursor and the disturbance and cursor were expected to be relatively weak.

The results revealed that all of the participants' responses matched the expected model across each tracking run (i.e., FR, TT1, & TT2). More specifically, the Percent Correct

(PCC) indices for all 72 disturbance-mouse relationships (D-M; 24 persons x 3 trials = 72 possible relationships) were the strongest compared with the 72 disturbance-cursor (D-C) and 72 mouse-cursor (M-C) relationships. As a reminder, the analysis computed pairwise comparisons (499,500 total) between the D-M movements to tally how many times the mouse movements occurred simultaneously with the disturbance values. This same pattern of analyses was conducted for the D-C and M-C relationships.

The results indicated that every person's responses were consistent with the proposed integrated model. Moreover, the data produced from these results clearly indicated and revealed the final cause in action. For example, individuals within the current experiment were first instructed that the goal of the study was simple, "*keep the cursor aligned to the target as much as you can, for as long as you can.*" If the individuals in the current experiment were behaving according to the final cause (i.e., cursor and target alignment), then the individuals should respond such that the mouse movements occur to counteract the disturbances so that the cursor and target are aligned.

Following the integrated model in Figure 3, the individual would then click "go" and enact the final cause such that he or she would begin to judge whether the cursor and target are aligned and then subsequently behave to either restore alignment or maintain the alignment. This process is represented within the feedback loop portion of the model in Figure 3, which is encased within the final cause plaque. As previously stated, this reasoning is simple; the sole reason this loop portion (i.e., the efficient cause process) occurs is in service to the final cause. To explicate this further, consider the results and output from the 'worst' run produced by Ruth (see Figure 6 above).

Ruth began the experiment in the same fashion as every other participant, she was instructed that the goal of the study was to "keep the cursor and target aligned as long as she could, as much as she could, for about thirty seconds." This is represented within the model with the researcher (square headed character in Figure 3) telling the participant the final cause (i.e., keep the cursor aligned with the target), which is represented with the callout bubble encasing the final cause plaque. Ruth understood the goal was to keep the cursor and target aligned, which is illustrated within the model with the callout thought bubble encompassing the final cause plaque. Ruth then began her first run by clicking “go” and proceeded to the task. At this point, Ruth immediately entered the feedback loop portion of the model, and we clearly see the outcome produced from her data. Specifically, the feedback loop portion of the model represents a series of efficient causes where Ruth perceived the cursor’s current location on the screen, then judged whether the cursor and target were aligned, and if not, counteracted the disturbances to restore the cursor line into alignment with the target line.

Examining Ruth’s data, we can interpret that the efficient cause process of the model was occurring since the PCC from the D-M relationship was the highest. Ruth was clearly counteracting the disturbances by moving the mouse in the opposite direction. As seen in the model, Ruth should have perceived the cursor’s location on the screen, then judged whether it was in alignment or not with the target. If the cursor was aligned, then Ruth did not move the mouse, but maintained the alignment. However, if Ruth perceived misalignment due to some disturbances, then she should have counteracted those disturbances by moving the mouse, which she did successfully for the majority of the run as exhibited by the high D-M PCC (87%) of her first run.

Ruth represents the worst run out of anyone within the current sample, and yet her D-M relationship is incredibly strong and is 30% higher than either the D-C or M-C relationships from the same run. Perhaps more impressive is that Ruth indicated that she was left-handed, though the study was only set up for a right-handed individual. Despite using her non-dominant hand, Ruth was still able to maintain alignment with the target and counteract the disturbances. What is most important, however, is that the process of Ruth counteracting the disturbances by moving the mouse only occurred due to the final cause (i.e., keeping the target and cursor aligned). This point is made clear when we observe the cursor output (green line) found in Figure 6. Examining the figure, the cursor data (the green line) is moving towards or around the 0 value. A value of 0 indicates that the target and cursor are in perfect alignment, therefore, the figure suggests that at all times Ruth was counteracting the disturbances to attempt to achieve the final cause.

As another example consider Figure 7. The final cause was changed such that in figure 7 some arbitrary point on the screen was used as a reference point (e.g., to the right of the target line). As can be seen, it is apparent the disturbances are being counteracted by moving the mouse, as the PCC produced for the D-M relationship is exceptionally high (~93%). This pattern indicates that the efficient cause process, counteracting the disturbances by moving the mouse, is occurring. One may even be tempted to state that the results produced from Figure 7 are identical to, and better than, those produced from Ruth's worst run as her D-M PCC was only near 87%. Unfortunately, this explanation would be insufficient, incomplete, and wrong. Ruth's run is still 'better' because her data demonstrates that the efficient causes (i.e., moving the mouse to counteract the disturbances) are occurring in service to the posited final cause (i.e., to maintain alignment). On the other hand, in the mock data used in Figure 7, some alternative final cause is at work, such that, the cursor data do not revolve around or approach 0 at any point, despite the efficient causes clearly operating. For these data, the final cause operating can only be understood by looking at both the PCC produced from the D-M relationship and the graphical output together. The high D-M relationship should be produced in service to the final cause, meaning the cursor data should end up close to 0, or at least trending around that 0 point, as we see across all individuals within the sample (see Figure 5 & 6).

To further demonstrate the point, suppose that an individual moved the mouse randomly throughout the duration of the task. The data produced from a randomized run might look like the mock data produced in either Figure 8a or Figure 8b. In both of these figures it is clear the individual is not following any set goal (unless the goal was to move the mouse randomly) as in both cases, the PCC computed for the D-M relationship is lower than that of the M-C relationship. This tells us that the cursor is moving in direct response to the sporadic movements of the mouse, and that the individual is in no way systematically counteracting the disturbances by moving the mouse.

Together, these example figures demonstrate the importance and need to look at the efficient cause relationships in service to the final cause. In all three of these cases, the PCC directly 'quantifies' the success of the efficient cause process, but the graphical outputs must also be interpreted. Namely, when we consider Ruth's graphical output in Figure 5b and the computed PCC from the D-M relationship, she moved the mouse in such a way to counteract the disturbances to ultimately attempt at maintaining alignment with the target line.

As argued in the introduction of the current paper, however, the input-output (I – O) assumption can be construed as the centermost assumption and is the most problematic issue. An overreliance upon the I – O assumption has led psychologists to purely focus upon understanding the generic inputs and outputs of psychological processes. As already elucidated by Dougherty (2013) and Wallace (1996) among others, such an understanding leads to an insufficient, incomplete, and in some cases inaccurate understanding of science and nature. If one were to only consider the PCC of the disturbance and mouse relationship, then one is only considering the efficient causes, which would be an insufficient, incomplete, and inaccurate understanding of the data from the PCT task. However, when one looks at the graphical output of the cursor's current position, alongside the computed PCC value, then one is clearly analyzing the efficient causes as they are occurring to bring about the final cause.

The PCT researcher could certainly continue to utilize the correlations between the D-M, D-C, and M-C relationship, alongside of the RMSE value and stability, as this information yields similar results. The conclusions remain identical in that the D-M relationship produces the strongest correlation out of the 3 relationships (D-M, D-C, & M-C) and the RMSE indicates the average deviation away from the referent (i.e., the target line or 0). Moreover, the PCT researcher could continue to model the PCT processes with the schematic diagrams utilized by Powers (1973) and others (see also Marken & Horth, 2011), as these models are still superior to the standard I – O model utilized by most psychologists. We argue, however, three primary benefits of departing from the standard research model and its accompanying philosophy (i.e., positivism), which will benefit the PCT researcher and greatly benefit the traditional psychologist that relies upon using the standard research model (i.e., the I – O model).

First, both the PCT researcher and traditional psychologist can greatly benefit from utilizing the novel integrated model procedure. These models are beneficial in that they depart from the inherent issues connected with philosophical positivism (e.g., the I – O assumption) and the models return the person to the center of investigation within psychological processes (see Grice, 2011; Lamiell & Slaney, 2020; Molennar, 2004). Importantly, these integrated models not only model the psychological processes at the level of the individual but are also accompanied by analyses at the level of the person (viz., OOM). Most importantly, these models clearly explicate the structures and dynamics of the psychological process under investigation as they are occurring within the person.

For the PCT researcher, the organism is the primary subject, as it is the organism who controls its perceptions of events. While the traditional PCT model is defined for persons, the models themselves are not humanistic in appearance. The PCT models, as mentioned previously, are likely products of Powers' previous background within electrical engineering as they are schematic in appearance. More importantly, however, the PCT models themselves do not have a sufficient representation for a final cause, as the reference signal (see Figure 2) only represents the final cause as initiator, but not as end.

From a data analysis standpoint, we argue that the results produced from the correlations themselves do not provide as much information as do the PCCs. For instance, the correlation only provides the strength of the relationship between the mouse, cursor, and disturbance, whereas the PCC provides not only the strength of the relationship, but the quantity of instances in which 1) the mouse was moved in response to the disturbances, 2) the cursor was moved in response to the disturbances, and 3) the cursor was moved in response to the mouse moving. This additional information informs the researcher of the exact percentage of each relationship so that one can clearly know how much stronger the relationship was compared to the other (e.g., Ruth's D-M PCC, 89%, from her FR was 30% stronger than either the D-C, 55%, or M-C, 56%, PCCs). It is important to note that all these benefits are applicable to both the PCT researcher and traditional psychologist. In both cases, the integrated models are superior to models produced by either researcher, though the models produced by PCT researchers are infinitely better than those produced under the I – O assumption (i.e., the traditional psychologist).

Second, utilizing the novel integrated model approach will produce more efficient model testing, theory development, and research progression for both the PCT researcher and traditional psychologist. The integrated model clearly defines all structures and processes occurring within a given psychological process, and appropriately tests them utilizing the novel person-centered effect size, the PCC. Using the PCC, one directly compares the results of one model with another. For example, within the current study, suppose we originally hypothesized that the mouse and cursor relationship should have been the strongest, as we reasoned that if the participant is moving the mouse, then the cursor on the screen would obviously have to move as well. Suppose we then built an integrated model that was similar to the one produced within Figure 3. In analyzing said model, we would clearly conclude that the M-C relationship does not yield the strongest relationship and is therefore not a valid 'mechanism' producing our results. Instead, what we might see is what we found within our results, the strongest PCCs would be those produced by the D-M relationship. Importantly, such an understanding can be regarded to as an *inference to best explanation*, which is a type of abduction in which the scientists compare two theories and accept the theory which produces the best results (see also Haig, 2005; 2014).

Using integrated models, a researcher can directly test two competing theories and determine which produces the highest PCC, thereby accepting one theory and rejecting the other (i.e., inference to best explanation). For instance, in our study if we competed the M-C model against the D-M model, we would take the D-M model as the *inference to best explanation*. The

D-M model produced the best results when compared with the other competing model. As another example, Grice and colleagues (2017) created and tested two competing integrated models to determine the best explanation for enhanced memory recall. In both cases, the creation and testing of two integrated models allows the researcher to determine whether one competing theory is superior or inferior to another, thereby progressing science.

In addition to this, researchers can systematically build upon and expand a given integrated model. For example, within PCT, one could expand the current model to determine whether additional disturbances (such as environmental noise or higher mouse DPI) produce meaningful changes to the D-M PCC. If a reduction in the PCC is found, then one can conclude that the addition of these model components resulted in a decrease to the PCC. More importantly, however, the utilization of these models allows for enhanced replicability. For example, one can create and test a model, which could then be taken and tested by another researcher. If an equivalent (or nearly equivalent) PCC is not found, then one might conclude that this effect was a product of chance or alter the model to determine where the failure to reproduce the results occurred. This would certainly be advantageous to any researcher, but especially now given the increasing concerns of reproducibility within psychological science (see Koole & Lakens, 2012; Nosek et al., 2018; Open Science Framework, 2015; Simons, 2014).

Finally, and most importantly, utilizing the integrated model and novel final cause modeling approach, the final cause is returned to investigation within psychology. Due to the overreliance upon a problematic philosophy, positivism, psychologists have unfortunately lost sight of the investigation into final causes (see Rychlak, 1988), and have solely relied upon the investigation and explanation of efficient cause processes (i.e., inputs and their resultant outputs). As already highlighted and demonstrated previously, a sole reliance upon efficient causes produces an unsatisfactory, incomplete, and in some cases an incorrect understanding of nature and psychological processes. Joseph Rychlak (1988) understood that final causality was extremely important when he relied upon such an understanding to develop his logical learning theory and William Powers (1973), perhaps unknowingly, additionally relied upon final causality with his explanation of perceptual control theory. Unfortunately, neither were successful in producing an adequate representation of a final cause as the first cause and last cause (i.e., end).

Utilizing the modeling technique developed from the current paper, psychologists will be able to invigorate psychology as a more rigorous science built upon Aristotelian philosophy (e.g., realism). In doing so, psychologists will no longer be limited by the insufficient and myopic explanations of inputs and their corresponding outputs. Rather, psychologists will be enabled to produce fruitful models and theories which restore the individual person to the center of investigation, offer inferences to best explanations, improve model testing and theory development, and most importantly, restore teleological (i.e., final causes) explanations to psychological science.

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FOOTNOTES

[1] Such as transcendental realism (Bhaskar, 2008), moderate realism (Grice, 2011; Wallace, 1996), modest realism (Sokal, 2010), naturalistic realism (Haig & Evers, 2015), critical scientific realism (Chirkov & Anderson, 2018), systematic realism (Hooker, 1987), and hylorealism (Bunge, 1993).

[2] For an overview of the issues with conceptualizing science as probabilistic, refer to the Probability Assumption within Arocha's (2020) paper entitled: Scientific Realism and the Issue of Variability in behavior (pp. 6-8).

[3] A critique of deductivism and falsification is beyond the scope of the current paper. However, detailed critiques and accompanying recommendations can be found within William Wallace's (1996) The Modeling of Nature, Jude Dougherty's (2013) The Nature of Scientific Exploration, Rom Harré's (1970) The Principles of Scientific Thinking, and Joseph Rychlak's (1988) The Psychology of Rigorous Humanism.

[4] Two translations of Aristotle's Physics and Metaphysics were utilized for all discussion of the four causes. 1) The Works of Aristotle by W.D. Ross as it appears in the Great Books of the Western World Volume 8: Aristotle, Volume I (Hutchins, 1952) and 2) A New Aristotle Reader by J.L. Ackrill (1987).

[5] In this specific example, however, the carpenter fashioning the wood into the stool can be understood as an efficient cause as well. The carpenter is directly responsible for manipulating

the material into the desired form and is seen as the source (i.e., the efficient cause) of the stool's production. It is important to note, however, that Aristotle would argue (see Phys. II.3, 195b 6–8) that the carpenter is not the single most explanatory efficient cause (i.e., not a per se cause; see Metaph. V.2, 1013b 34 –1014a 4) for the process. By this it is meant that the carpenter is not actually the first cause that initiates this process (i.e., per se cause), instead it is the skill of carpentry that is the foremost efficient cause in the process. Simply stated, the carpenter must first obtain the knowledge of the skill, in this case carpentry, before being able to manipulate the material into the desired form. For Aristotle, differentiating between primary efficient causes (i.e., the per se cause) and secondary efficient causes is critical to providing general explanations of things (i.e., scientific knowledge). By choosing the skill of carpentry as the single most explanatory factor in the stool's production, Aristotle is able to provide a naturalistic explanation of the nature of constructing stools without reliance upon the desires, beliefs, or intentions of a specific agent (i.e., the carpenter). Meaning the intentions, beliefs, or desires of the individual carpenter producing the wooden stool are not required to understand the process by which 'general' stools come to be (see also, Falcon 2019). This is not to say that intentions, beliefs, or desires are not important components, rather it is to say that scientific knowledge, according to Aristotle (see Phys. 195b 21–25), is achieved through understanding the general causes of things (see Falcon, 2019; Grice, 2011; Wallace, 1996). In other words, scientific knowledge is obtained when one understands what is typical in nature (see also Grice, 2014). For example, it is typical that stools have a flat base to sit upon and a number of legs fashioned beneath the flat base. By comparison, it may be a specific carpenter's preference that the stool has three legs and a square base, however, preferences do not need to be considered to understand the 'general' process of how a stool came to be produced

[6] For a complete history of the treatment of the four causes in scientific investigation throughout western history consult the extraordinarily detailed table within Joseph F. Rychlak's (1988) book, The Psychology of Rigorous Humansism (pp. 8-31).

[7] The c-value is interpreted as a 'chance' statistic. The c-value is computed by randomly shuffling the data and re-running the analysis to determine if the observed PCC can be produced by randomization (see Grice, 2021). For these data, 1,000 iterations were utilized across every analysis. The c-value can be directly interpreted as a 'plausability' value to indicate how likely the observed PCC can be produced from dumb luck or chance alone.

APPENDICES

APPENDIX A – TABLES

Table 1

First Run Results for Males and Females

Participant	D-M Relationship			D-C Relationship			M-C Relationship			RMS	Stability
	PCC	C-Value	*r*	PCC	C-Value	*r*	PCC	C-Value	*r*		
Males											
Noah	89.79	< 0.001	-0.884	62.71	< 0.001	-0.02	69.23	< 0.001	0.48	11.47	2.84
John	91.22	< 0.001	-0.995	61.77	< 0.001	-0.41	64.26	< 0.001	0.50	2.92	12.04
Daniel	90.94	< 0.001	-0.989	53.44	0.001	-0.15	56.79	< 0.001	0.29	4.01	9.44
Jeremiah	91.11	< 0.001	-0.993	66.29	< 0.001	-0.58	67.50	< 0.001	0.67	4.22	9.32
Paul	94.46	< 0.001	-0.999	63.87	< 0.001	-0.45	64.31	< 0.001	0.50	1.43	22.94
Ezekiel	95.03	< 0.001	-0.996	66.03	< 0.001	-0.46	67.49	< 0.001	0.54	2.35	13.47
Aaron	95.55	< 0.001	-0.997	57.17	< 0.001	-0.23	57.98	< 0.001	0.30	1.67	18.74
Joshua	93.45	< 0.001	-0.994	56.92	< 0.001	-0.21	58.64	< 0.001	0.31	2.59	12.39
Elijah	96.38	< 0.001	-0.997	66.05	< 0.001	-0.49	67.18	< 0.001	0.55	2.13	16.37
Luke	96.06	< 0.001	-0.995	59.27	< 0.001	-0.19	60.58	< 0.001	0.30	2.58	13.20
Isaiah	94.80	< 0.001	-0.995	72.99	< 0.001	-0.69	75.16	< 0.001	0.76	4.08	9.91
Matthew	94.18	< 0.001	-0.994	59.99	< 0.001	-0.31	62.38	< 0.001	0.41	2.73	12.22
Females											
Miriam	92.93	< 0.001	-0.992	48.70	0.88	0.11	50.65	0.002	0.02	2.85	11.03
Sarah	94.20	< 0.001	-0.992	57.44	< 0.001	-0.21	60.09	< 0.001	0.33	3.02	10.69
Tabitha	92.00	< 0.001	-0.990	56.39	< 0.001	-0.26	59.77	< 0.001	0.39	4.05	9.37
Rachel	95.66	< 0.001	-0.995	56.16	< 0.001	-0.18	57.97	< 0.001	0.27	2.50	13.91
Deborah	89.32	< 0.001	-0.984	46.46	1.00	-0.05	49.80	< 0.001	0.23	4.51	7.74
Ruth	87.09	< 0.001	-0.986	54.83	< 0.001	-0.25	56.36	< 0.001	0.41	5.11	7.87
Mary	94.15	< 0.001	-0.994	57.85	< 0.001	-0.28	61.01	< 0.001	0.39	3.03	11.92
Esther	93.98	< 0.001	-0.992	45.53	1.00	0.18	48.23	0.51	-0.06	2.72	11.23
Leah	93.92	< 0.001	-0.997	55.07	< 0.001	-0.16	55.96	< 0.001	0.24	2.19	16.75
Martha	93.08	< 0.001	-0.988	60.38	< 0.001	-0.37	61.34	< 0.001	0.51	3.73	8.36
Priscilla	93.17	< 0.001	-0.993	51.55	0.06	-0.10	53.61	< 0.001	0.21	2.56	12.17
Anna	90.47	< 0.001	-0.982	51.81	0.04	-0.16	56.26	< 0.001	0.34	4.65	7.29

Note. These values represent the complete results for the first run. PCC = Percent Correct Classification, RMS = RMSE.

Table 2

Test Trial 1 Results for Males and Females

Participant	D-M Relationship			D-C Relationship			M-C Relationship			RMS	Stability
	PCC	C-Value	*r*	PCC	C-Value	*r*	PCC	C-Value	*r*		
Males											
Noah	94.62	< 0.001	-0.995	65.47	< 0.001	-0.47	67.42	< 0.001	0.56	3.02	12.08
John	94.05	< 0.001	-0.995	48.70	0.88	0.06	50.38	0.004	0.05	2.67	13.99
Daniel	93.37	< 0.001	-0.990	50.65	0.25	0.004	53.25	< 0.001	0.14	3.37	10.07
Jeremiah	95.27	< 0.001	-0.998	48.73	0.88	0.03	49.36	0.09	0.03	1.31	24.48
Paul	95.64	< 0.001	-0.996	56.29	< 0.001	-0.19	58.11	< 0.001	0.28	2.25	14.85
Ezekiel	96.00	< 0.001	-0.997	56.71	< 0.001	-0.20	57.80	< 0.001	0.28	2.08	16.83
Aaron	94.16	< 0.001	-0.996	46.16	1.00	0.15	46.96	0.68	-0.05	2.13	14.85
Joshua	95.12	< 0.001	-0.996	66.94	< 0.001	-0.51	68.03	< 0.001	0.58	2.34	13.75
Elijah	95.66	< 0.001	-0.996	55.82	< 0.001	-0.22	57.63	< 0.001	0.31	2.14	14.39
Luke	94.72	< 0.001	-0.997	59.39	< 0.001	-0.32	60.29	< 0.001	0.39	2.16	17.12
Isaiah	93.69	< 0.001	-0.990	58.85	< 0.001	-0.31	61.17	< 0.001	0.44	3.57	9.38
Matthew	95.66	< 0.001	-0.997	52.89	0.001	-0.09	54.16	< 0.001	0.16	1.88	19.42
Females											
Miriam	94.63	< 0.001	-0.995	55.61	< 0.001	-0.14	57.81	< 0.001	0.24	2.65	13.86
Sarah	93.86	< 0.001	-0.996	59.67	< 0.001	-0.30	61.83	< 0.001	0.38	2.96	14.31
Tabitha	93.13	< 0.001	-0.993	57.38	< 0.001	-0.24	59.34	< 0.001	0.35	2.74	11.32
Rachel	95.60	< 0.001	-0.995	53.19	< 0.001	-0.17	54.97	< 0.001	0.26	2.37	14.21
Deborah	91.10	< 0.001	-0.992	51.24	0.11	-0.09	52.47	< 0.001	0.22	2.83	10.88
Ruth	92.07	< 0.001	-0.992	59.88	< 0.001	-0.40	61.36	< 0.001	0.52	3.17	9.79
Mary	95.17	< 0.001	-0.995	61.55	< 0.001	-0.27	63.46	< 0.001	0.36	2.30	13.79
Esther	93.90	< 0.001	-0.997	64.58	< 0.001	-0.44	65.97	< 0.001	0.52	2.55	14.90
Leah	94.34	< 0.001	-0.996	50.67	0.25	-0.05	52.20	< 0.001	0.14	2.46	14.85
Martha	92.18	< 0.001	-0.991	58.02	< 0.001	-0.25	60.32	< 0.001	0.37	3.62	10.23
Priscilla	94.18	< 0.001	-0.989	54.92	< 0.001	-0.08	58.12	< 0.001	0.23	3.29	9.40
Anna	93.56	< 0.001	-0.990	63.89	< 0.001	-0.44	67.59	< 0.001	0.56	3.67	8.76

Note. These values represent the complete results for test trial 1. PCC = Percent Correct Classification, RMS = RMSE.

Table 3

Test Trial 2 Results for Males and Females

Participant	D-M Relationship			D-C Relationship			M-C Relationship			RMS	Stability
	PCC	C-Value	*r*	PCC	C-Value	*r*	PCC	C-Value	*r*		
Males											
Noah	95.47	< 0.001	-0.996	55.27	< 0.001	-0.14	56.84	< 0.001	0.23	2.02	15.33
John	93.13	< 0.001	-0.990	57.75	< 0.001	-0.33	61.64	< 0.001	0.46	3.41	9.21
Daniel	95.29	< 0.001	-0.996	50.65	0.24	0.07	52.43	< 0.001	0.02	2.18	15.10
Jeremiah	94.38	< 0.001	-0.996	63.39	< 0.001	-0.43	65.23	< 0.001	0.51	2.33	13.82
Paul	95.96	< 0.001	-0.997	53.05	0.003	-0.10	54.32	< 0.001	0.18	1.76	17.22
Ezekiel	94.59	< 0.001	-0.997	47.15	0.995	0.05	48.51	0.29	0.03	1.78	17.33
Aaron	95.39	< 0.001	-0.997	52.41	0.008	-0.09	53.42	< 0.001	0.17	2.14	17.12
Joshua	94.07	< 0.001	-0.995	58.83	< 0.001	-0.26	60.38	< 0.001	0.36	2.29	13.69
Elijah	96.00	< 0.001	-0.995	56.02	< 0.001	-0.24	57.59	< 0.001	0.34	2.53	14.01
Luke	96.50	< 0.001	-0.997	54.50	< 0.001	-0.16	55.76	< 0.001	0.23	1.89	18.29
Isaiah	95.56	< 0.001	-0.995	64.59	< 0.001	-0.44	66.08	< 0.001	0.53	2.95	12.72
Matthew	95.49	< 0.001	-0.997	45.69	1.00	0.13	47.34	0.84	-0.05	1.76	17.50
Females											
Miriam	94.10	< 0.001	-0.993	49.53	0.66	0.05	51.84	< 0.001	0.07	3.07	11.64
Sarah	94.81	< 0.001	-0.996	55.80	< 0.001	-0.27	57.27	< 0.001	0.36	2.18	14.71
Tabitha	91.43	< 0.001	-0.989	50.63	0.27	0.07	53.55	< 0.001	0.08	3.26	9.56
Rachel	92.56	< 0.001	-0.992	54.04	< 0.001	-0.24	56.19	< 0.001	0.36	3.49	10.51
Deborah	92.82	< 0.001	-0.986	49.03	0.79	0.05	51.20	< 0.001	0.12	3.75	8.41
Ruth	92.10	< 0.001	-0.992	62.17	< 0.001	-0.39	63.98	< 0.001	0.50	3.19	9.91
Mary	94.90	< 0.001	-0.998	53.16	0.001	-0.18	53.93	< 0.001	0.24	1.39	23.73
Esther	93.17	< 0.001	-0.996	44.48	1.00	0.14	45.93	0.88	-0.05	1.98	15.33
Leah	93.98	< 0.001	-0.995	46.43	0.999	0.07	49.14	0.22	0.03	2.25	14.16
Martha	89.96	< 0.001	-0.988	57.09	< 0.001	-0.30	60.59	< 0.001	0.44	3.67	8.65
Priscilla	94.58	< 0.001	-0.988	59.69	< 0.001	-0.36	62.41	< 0.001	0.50	4.79	8.13
Anna	94.31	< 0.001	-0.994	59.37	< 0.001	-0.29	61.33	< 0.001	0.39	2.98	12.44

Note. These values represent the complete results for test trial 2. PCC = Percent Correct Classification, RMS = RMSE.

Table 4

Person-Centered PCC Descriptive Statistics from the Disturbance & Mouse Relationship

Participant	Min PCC	Max PCC	Median PCC	Mean PCC	SD PCC
Males					
Noah	89.79	95.47	94.62	93.29	2.50
John	91.22	94.05	93.13	92.80	1.18
Daniel	90.94	95.29	93.37	93.20	1.78
Jeremiah	91.11	95.27	94.38	93.59	1.79
Paul	94.46	95.96	95.64	95.35	0.65
Ezekiel	94.59	96.00	95.03	95.21	0.59
Aaron	94.16	95.55	95.39	95.03	0.62
Joshua	93.45	95.12	94.07	94.21	0.69
Elijah	95.66	96.38	96.00	96.01	0.29
Luke	94.72	96.50	96.06	95.76	0.76
Isaiah	93.69	95.56	94.80	94.68	0.77
Matthew	94.18	95.66	95.49	95.11	0.66
Females					
Miriam	92.93	94.63	94.10	93.89	0.71
Sarah	93.86	94.81	94.20	94.29	0.39
Tabitha	91.43	93.13	92.00	92.19	0.71
Rachel	92.56	95.66	95.60	94.61	1.45
Deborah	89.32	92.82	91.10	91.08	1.43
Ruth	87.09	92.10	92.07	90.42	2.35
Mary	94.15	95.17	94.90	94.74	0.43
Esther	93.17	93.98	93.90	93.68	0.36
Leah	93.92	94.34	93.98	94.08	0.19
Martha	89.96	93.08	92.18	91.74	1.31
Priscilla	93.17	94.58	94.18	93.98	0.59
Anna	90.47	94.31	93.56	92.78	1.66

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the PCC for the disturbance-mouse relationship across their first run, test trial 1, and test trial 2 output.

PCC = Percent Correct Classification

Min = minimum value

Max = maximum value

SD = standard deviation

Table 5

Person-Centered PCC Descriptive Statistics from the Disturbance & Cursor Relationship

Participant	Min PCC	Max PCC	Median PCC	Mean PCC	SD PCC
Males					
Noah	55.27	65.47	62.71	61.15	4.31
John	48.70	61.77	57.75	56.07	5.47
Daniel	50.65	53.44	50.65	51.58	1.32
Jeremiah	48.73	66.29	63.39	59.47	7.69
Paul	53.05	63.87	56.29	57.74	4.53
Ezekiel	47.15	66.03	56.71	56.63	7.71
Aaron	46.16	57.17	52.41	51.91	4.51
Joshua	56.92	66.94	58.83	60.90	4.34
Elijah	55.82	66.05	56.02	59.30	4.78
Luke	54.50	59.39	59.27	57.72	2.28
Isaiah	58.85	72.99	64.59	65.48	5.81
Matthew	45.69	59.99	52.89	52.86	5.84
Females					
Miriam	48.70	55.61	49.53	51.28	3.08
Sarah	55.80	59.67	57.44	57.64	1.59
Tabitha	50.63	57.38	56.39	54.80	2.98
Rachel	53.19	56.16	54.04	54.46	1.25
Deborah	46.46	51.24	49.03	48.91	1.95
Ruth	54.83	62.17	59.88	58.96	3.07
Mary	53.16	61.55	57.85	57.52	3.43
Esther	44.48	64.58	45.53	51.53	9.24
Leah	46.43	55.07	50.67	50.72	3.53
Martha	57.09	60.38	58.02	58.50	1.38
Priscilla	51.55	59.69	54.92	55.39	3.34
Anna	51.81	63.89	59.37	58.36	4.98

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the PCC for the disturbance-cursor relationship across their first run, test trial 1, and test trial 2 output.

PCC = Percent Correct Classification

Min = minimum value

Max = maximum value

SD = standard deviation

Table 6

Person-Centered PCC Descriptive Statistics from the Mouse & Cursor Relationship

Participant	Min PCC	Max PCC	Median PCC	Median PCC	SD PCC
Males					
Noah	56.84	69.23	67.42	64.50	5.46
John	50.38	64.26	61.64	58.76	6.02
Daniel	52.43	56.79	53.25	54.16	1.89
Jeremiah	49.36	67.50	65.23	60.70	8.07
Paul	54.32	64.31	58.11	58.91	4.12
Ezekiel	48.51	67.49	57.80	57.93	7.75
Aaron	46.96	57.98	53.42	52.79	4.52
Joshua	58.64	68.03	60.38	62.35	4.08
Elijah	57.59	67.18	57.63	60.80	4.51
Luke	55.76	60.58	60.29	58.88	2.21
Isaiah	61.17	75.16	66.08	67.47	5.80
Matthew	47.34	62.38	54.16	54.63	6.15
Females					
Miriam	50.65	57.81	51.84	53.43	3.13
Sarah	57.27	61.83	60.09	59.73	1.88
Tabitha	53.55	59.77	59.34	57.55	2.84
Rachel	54.97	57.97	56.19	56.38	1.23
Deborah	49.80	52.47	51.20	51.16	1.09
Ruth	56.36	63.98	61.36	60.57	3.16
Mary	53.93	63.46	61.01	59.47	4.04
Esther	45.93	65.97	48.23	53.38	8.95
Leah	49.14	55.96	52.20	52.43	2.79
Martha	60.32	61.34	60.59	60.75	0.43
Priscilla	53.61	62.41	58.12	58.05	3.59
Anna	56.26	67.59	61.33	61.73	4.63

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the PCC for the mouse-cursor relationship across their first run, test trial 1, and test trial 2 output.

PCC = Percent Correct Classification

Min = minimum value

Max = maximum value

SD = standard deviation

Table 7

Person-Centered Correlation Descriptive Statistics from the Disturbance & Mouse Relationship

Participant	Weakest *r*	Strongest *r*	Median *r*	Mean *r*	SD *r*
Males					
Noah	-0.884	-0.996	-0.995	-0.958	0.053
John	-0.990	-0.995	-0.995	-0.993	0.002
Daniel	-0.989	-0.996	-0.990	-0.992	0.003
Jeremiah	-0.993	-0.998	-0.996	-0.996	0.002
Paul	-0.996	-0.999	-0.997	-0.997	0.001
Ezekiel	-0.996	-0.997	-0.997	-0.997	< 0.001
Aaron	-0.996	-0.997	-0.997	-0.997	< 0.001
Joshua	-0.994	-0.996	-0.995	-0.995	0.001
Elijah	-0.995	-0.997	-0.996	-0.996	0.001
Luke	-0.995	-0.997	-0.997	-0.996	0.001
Isaiah	-0.990	-0.995	-0.995	-0.993	0.002
Matthew	-0.994	-0.997	-0.997	-0.996	0.001
Females					
Miriam	-0.992	-0.995	-0.993	-0.993	0.001
Sarah	-0.992	-0.996	-0.996	-0.995	0.002
Tabitha	-0.989	-0.993	-0.990	-0.991	0.002
Rachel	-0.992	-0.995	-0.995	-0.994	0.001
Deborah	-0.984	-0.992	-0.986	-0.987	0.003
Ruth	-0.986	-0.992	-0.992	-0.990	0.003
Mary	-0.994	-0.998	-0.995	-0.996	0.002
Esther	-0.992	-0.997	-0.996	-0.995	0.002
Leah	-0.995	-0.997	-0.996	-0.996	0.001
Martha	-0.988	-0.991	-0.988	-0.989	0.001
Priscilla	-0.988	-0.993	-0.989	-0.990	0.002
Anna	-0.982	-0.994	-0.990	-0.989	0.005

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the correlation coefficients for the disturbance-mouse relationship across their first run, test trial 1, and test trial 2 output.

r = Pearson's correlation coefficient

Min = minimum value

Max = maximum value

SD = standard deviation

Table 8

Person-Centered Correlation Descriptive Statistics from the Disturbance & Cursor Relationship

Participant	Weakest *r*	Strongest *r*	Median *r*	Mean *r*	SD *r*
Males					
Noah	-0.02	-0.47	-0.14	-0.21	0.19
John	0.06	-0.41	-0.33	-0.23	0.20
Daniel	0.07	-0.15	-0.004	-0.03	0.09
Jeremiah	0.03	-0.58	-0.43	-0.33	0.26
Paul	-0.10	-0.45	-0.19	-0.24	0.15
Ezekiel	0.05	-0.46	-0.20	-0.21	0.21
Aaron	0.15	-0.23	-0.09	-0.06	0.16
Joshua	-0.21	-0.51	-0.26	-0.33	0.13
Elijah	-0.22	-0.49	-0.24	-0.32	0.12
Luke	-0.16	-0.32	-0.19	-0.23	0.07
Isaiah	-0.31	-0.69	-0.44	-0.48	0.16
Matthew	0.13	-0.31	-0.09	-0.09	0.18
Females					
Miriam	0.11	-0.14	0.05	0.01	0.11
Sarah	-0.21	-0.30	-0.27	-0.26	0.04
Tabitha	0.07	-0.26	-0.24	-0.14	0.15
Rachel	-0.17	-0.24	-0.18	-0.20	0.03
Deborah	0.05	-0.09	-0.05	-0.03	0.06
Ruth	-0.25	-0.40	-0.39	-0.35	0.07
Mary	-0.18	-0.28	-0.27	-0.25	0.04
Esther	0.18	-0.44	0.14	-0.04	0.28
Leah	0.07	-0.16	-0.05	-0.05	0.10
Martha	-0.25	-0.37	-0.30	-0.30	0.05
Priscilla	-0.08	-0.36	-0.10	-0.18	0.13
Anna	-0.16	-0.44	-0.29	-0.30	0.12

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the correlation coefficients for the disturbance-cursor relationship across their first run, test trial 1, and test trial 2 output.

r = Pearson's correlation coefficient

Min = minimum value

Max = maximum value

SD = standard deviation

Table 9

Person-Centered Correlation Descriptive Statistics from the Mouse & Cursor Relationship

Participant	Weakest *r*	Strongest *r*	Median *r*	Mean *r*	SD *r*
Males					
Noah	0.23	0.56	0.48	0.42	0.14
John	0.05	0.50	0.46	0.34	0.21
Daniel	0.02	0.29	0.14	0.15	0.11
Jeremiah	0.03	0.67	0.51	0.40	0.27
Paul	0.18	0.50	0.28	0.32	0.13
Ezekiel	0.03	0.54	0.28	0.28	0.21
Aaron	-0.05	0.30	0.17	0.14	0.15
Joshua	0.31	0.58	0.36	0.42	0.12
Elijah	0.31	0.55	0.34	0.40	0.11
Luke	0.23	0.39	0.30	0.31	0.07
Isaiah	0.44	0.76	0.53	0.57	0.13
Matthew	-0.05	0.41	0.16	0.17	0.19
Females					
Miriam	0.02	0.24	0.07	0.11	0.10
Sarah	0.33	0.38	0.36	0.36	0.02
Tabitha	0.08	0.39	0.35	0.28	0.14
Rachel	0.26	0.36	0.27	0.30	0.05
Deborah	0.12	0.23	0.22	0.19	0.05
Ruth	0.41	0.52	0.50	0.48	0.05
Mary	0.24	0.39	0.36	0.33	0.06
Esther	-0.06	0.52	-0.05	0.14	0.27
Leah	0.03	0.24	0.14	0.14	0.09
Martha	0.37	0.51	0.44	0.44	0.06
Priscilla	0.21	0.50	0.23	0.31	0.13
Anna	0.34	0.56	0.39	0.43	0.09

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the correlation coefficients for the mouse-cursor relationship across their first run, test trial 1, and test trial 2 output.

r = Pearson's correlation coefficient

Min = minimum value

Max = maximum value

SD = standard deviation

Table 10

Person-Centered Root Mean Squared Descriptive Statistics

Participant	Min RMSE	Max RMSE	Median RMSE	Mean RMSE	SD RMSE
Males					
Noah	2.02	11.47	3.02	5.50	4.24
John	2.67	3.41	2.92	3.00	0.30
Daniel	2.18	4.01	3.37	3.18	0.76
Jeremiah	1.31	4.22	2.33	2.62	1.20
Paul	1.43	2.25	1.76	1.81	0.34
Ezekiel	1.78	2.35	2.08	2.07	0.23
Aaron	1.67	2.14	2.13	1.98	0.22
Joshua	2.29	2.59	2.34	2.41	0.13
Elijah	2.13	2.53	2.14	2.27	0.19
Luke	1.89	2.58	2.16	2.21	0.28
Isaiah	2.95	4.08	3.57	3.53	0.46
Matthew	1.76	2.73	1.88	2.12	0.43
Females					
Miriam	2.65	3.07	2.85	2.86	0.17
Sarah	2.18	3.02	2.96	2.72	0.38
Tabitha	2.74	4.05	3.26	3.35	0.54
Rachel	2.37	3.49	2.50	2.79	0.50
Deborah	2.83	4.51	3.75	3.70	0.69
Ruth	3.17	5.11	3.19	3.83	0.91
Mary	1.39	3.03	2.30	2.24	0.67
Esther	1.98	2.72	2.55	2.42	0.31
Leah	2.19	2.46	2.25	2.30	0.11
Martha	3.62	3.73	3.67	3.68	0.04
Priscilla	2.56	4.79	3.29	3.55	0.93
Anna	2.98	4.65	3.67	3.77	0.68

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the Root Mean Squared Error (RMSE) across their first run, test trial 1, and test trial 2 output. RMSE is the average difference of the controlled variable (the cursor) from the target. Lower RMSE values indicate better control over the cursor in reference to the target.

RMS = Root Mean Squared Error

Min = minimum value

Max = maximum value

SD = standard deviation

Table 11

Person-Centered Stability Descriptive Statistics

Participant	Min Stability	Max Stability	Median Stability	Mean Stability	SD Stability
Males					
Noah	2.84	15.34	12.08	10.08	5.29
John	9.21	13.99	12.04	11.75	1.96
Daniel	9.44	15.10	10.07	11.54	2.53
Jeremiah	9.32	24.48	13.82	15.87	6.36
Paul	14.85	22.94	17.22	18.34	3.39
Ezekiel	13.47	17.33	16.83	15.88	1.72
Aaron	14.85	18.74	17.12	16.90	1.60
Joshua	12.39	13.75	13.69	13.28	0.63
Elijah	14.01	16.38	14.39	14.92	1.04
Luke	13.20	18.29	17.12	16.20	2.18
Isaiah	9.38	12.72	9.91	10.67	1.47
Matthew	12.22	19.42	17.50	16.38	3.04
Females					
Miriam	11.03	13.86	11.64	12.18	1.22
Sarah	10.69	14.71	14.31	13.24	1.81
Tabitha	9.37	11.32	9.56	10.08	0.88
Rachel	10.51	14.21	13.91	12.88	1.68
Deborah	7.74	10.88	8.41	9.01	1.35
Ruth	7.87	9.91	9.79	9.19	0.93
Mary	11.92	23.73	13.79	16.48	5.18
Esther	11.23	15.33	14.91	13.82	1.84
Leah	14.16	16.75	14.85	15.25	1.09
Martha	8.36	10.23	8.65	9.08	0.82
Priscilla	8.13	12.17	9.41	9.90	1.69
Anna	7.29	12.44	8.76	9.50	2.17

Note. These values are each individual's minimum, maximum, median, average, and standard deviation from the Stability across their first run, test trial 1, and test trial 2 output. Stability is equivalent to the square root of the expected variation divided by the observed variation. Where expected variation is the combined variance of the mouse and disturbance output and observed variation is the variance of the cursor output. Higher Stability values indicate greater control over the cursor.

Min = minimum value

Max = maximum value

SD = standard deviation

Table 12

Qualitative Responses for All Individuals

Participant	Response
Males	
Noah	At the beginning the cursor would automatically move to one direction very slightly so I slightly moved the mouse the opposite way of this. As the trail went on the cursor would move more intensely and I adjusted the force I used to move the mouse accordingly.
John	I choose to move the curser slowly because the bottom line would move left or right at a slow pace.
Daniel	Because the bottom line should be aligned with the upper stable line, I imagined as if the upper line is my 4.0 GPA which is my current goal. Eventually I was trying so hard to reach my goal which is in this case a 4.0 GPA.
Jeremiah	To keep the lines stacked and even with each other. Counteracting the bottom line was the only way to keep it balanced so that is why I stuck with doing so.
Paul	I had one main goal in mind and that was to keep the lines aligned to the best of may ability. When I felt the bottom line slowly start moving to the left, I counter acted and started moving the mouse to the right. And vise versa to when the line moved to the right.
Ezekiel	I attempted to counter the movement of the cursor in the direction it was headed and the amount I thought it was accelerating.
Aaron	I moved the cursor to counteracts the movements of the line of the screen.
Joshua	Do to the resistance of the movement of the line, I was able to counteract the movement by moving the line the opposite way of the direction it was going. Depending on the speed of the movement of the line effected the movement to which I moved the mouse.
Elijah	I was trying to compensate for the movement of the cursor, as if it was being blown in the wind. When the lateral movement seemed to get more intense, I'd try to intensify how I counter-moved the cursor, without overshooting. It got harder as the test went on.
Luke	I moved the cursor to counteract the automated movement. For example, when the cursor moved to the right I had to counteract it by moving it to the left which allowed the line to stay near the set line. Same thing applies for when the bottom line was forced to move to the left.
Isaiah	Because I noticed the pattern of movement was shifting so I attempted to counter the magnitude of movement.
Matthew	I attempted to utilize my wrist in a manner that would allow me to keep stability and ensure that the line stayed in the middle.

Table 12 (*continued*)

Participant	Response
Females	
Miriam	I chose to move the cursor as little as possible when the line below was moving slowly and when the line below was moving quickly, I moved the cursor in short swift bursts to try and get it back under the line above as quickly as possible.
Sarah	Because I wanted to keep the lines in line.
Tabitha	I moved the cursor towards the center of the screen even when the cursor would move itself in the opposite direction of the desired action. For example, for about half of the trial the cursor would float the left of center, but I would prompt it to go to the right towards the target.
Rachel	I moved the cursor when it was counteracted in order to follow the center line. I believed there was a pattern to the movement so I was able to predict the force in order to get the cursor to stay in the middle.
Deborah	When the cursor moved too far to the right, I moved it to the left to align in it with the black mark above in the center. When the cursor moved too far to the left, I moved it to the right to align in it with the black mark above in the center.
Ruth	To try to make them align, I moved the cursor the way I did. I also noticed that the cursor would move away in a particular direction – slow at first and then faster – so, in order to keep it aligned I had to predict its direction and move it the other direction before it got too far and too fast.
Mary	After aligning the moving line with the stationary line, the system would pull the moving line away either to the left or right of the stationary line. I would move the cursor in the opposite direction to realign the moving line with the stationary line. So when it began to move left I would move the cursor right and vice versa.
Esther	I MOVED THE CURSER BACK THE OPPOSITE DIRECTION THE LINE WAS GOINING AND I COULD TELL WHEN IT AS ABOUT TO START GOING THE OTHER DIRECTION.
Leah	When the line moved to the left, I moved it back to the right in order to realign the two lines. And when it moved to the right, I moved it back to the left. I knew that it would move left first and then switch to moving right at some point during the 30 seconds and then switch back to moving left, so I prepared myself for each of those changes to move it back into alignment.
Martha	I moved the cursor when it was going to the left I pushed the mouse to the right. I thought this would balance it out and pull the cursor the direction I wanted it to go. When the line was moving towards the right I moved my cursor to the left. I thought of it as a push and pull system.
Priscilla	I moved it back the opposite way to try and realign the cursor with the line to keep them together.
Anna	When the cursor moved to the right, I moved it back to the left in order to balance it out and keep it in the middle. Same for the other direction, when it moved to the left, I moved it back to the right to try to keep it in the middle. When it moved slowly one direction, I moved it slowly the other. When it moved faster, I had to move it in the opposite direction faster.

APPENDIX B – FIGURES

Figure 1

A Conceptual Image of the Nature of Control Task

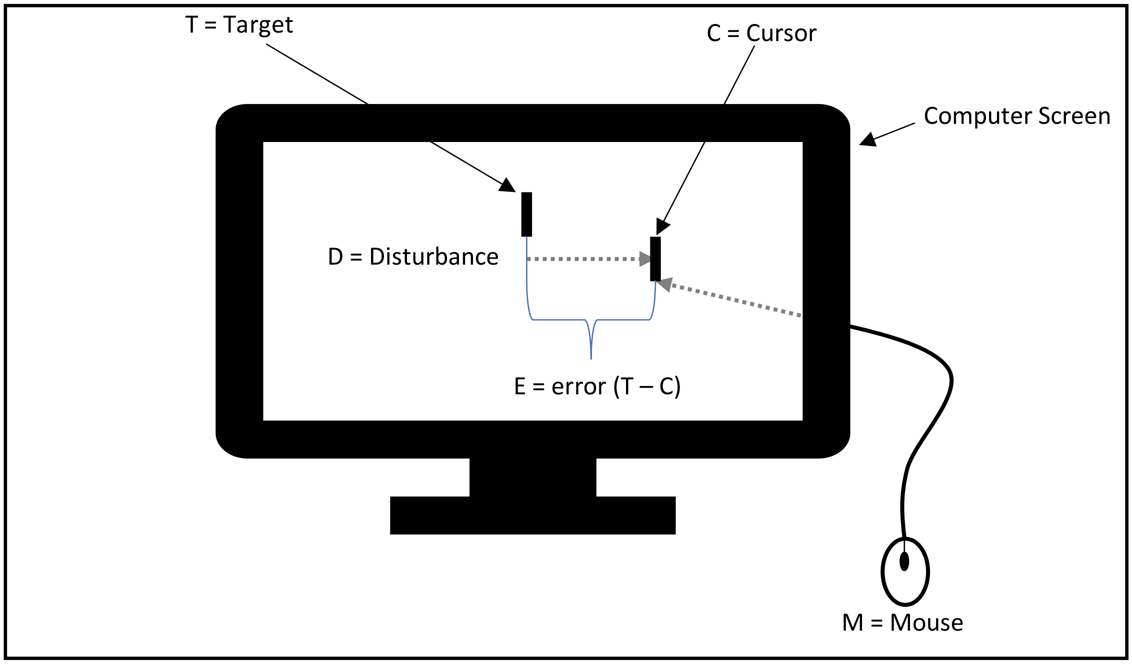


Figure 2

The Basic Features of a PCT Negative Feedback Loop

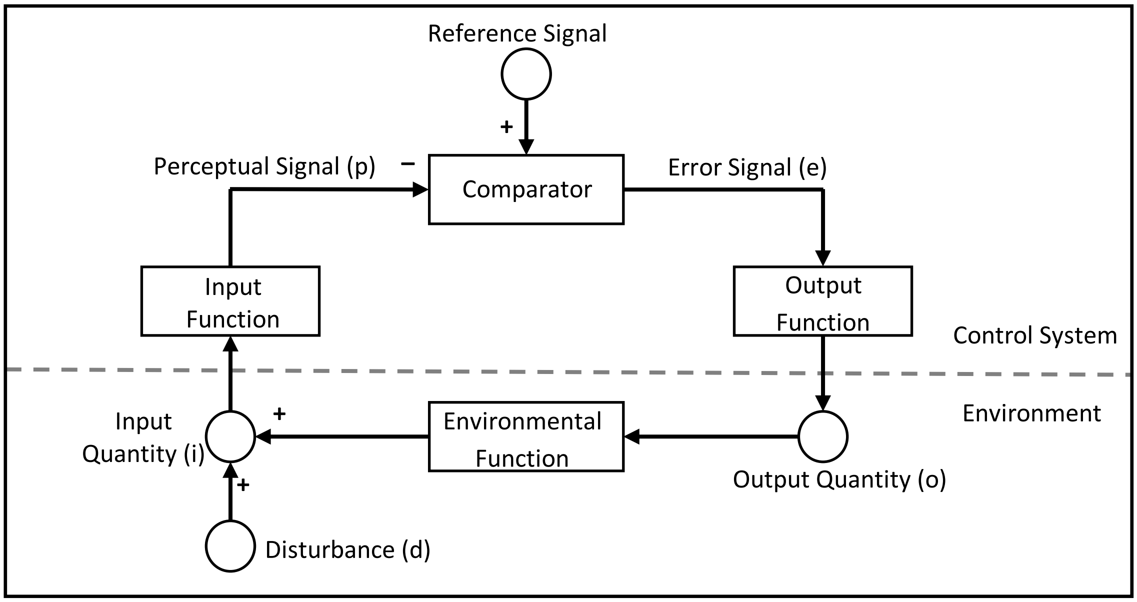


Figure 3
The Integrated Model of the Perceptual Control Theory Task

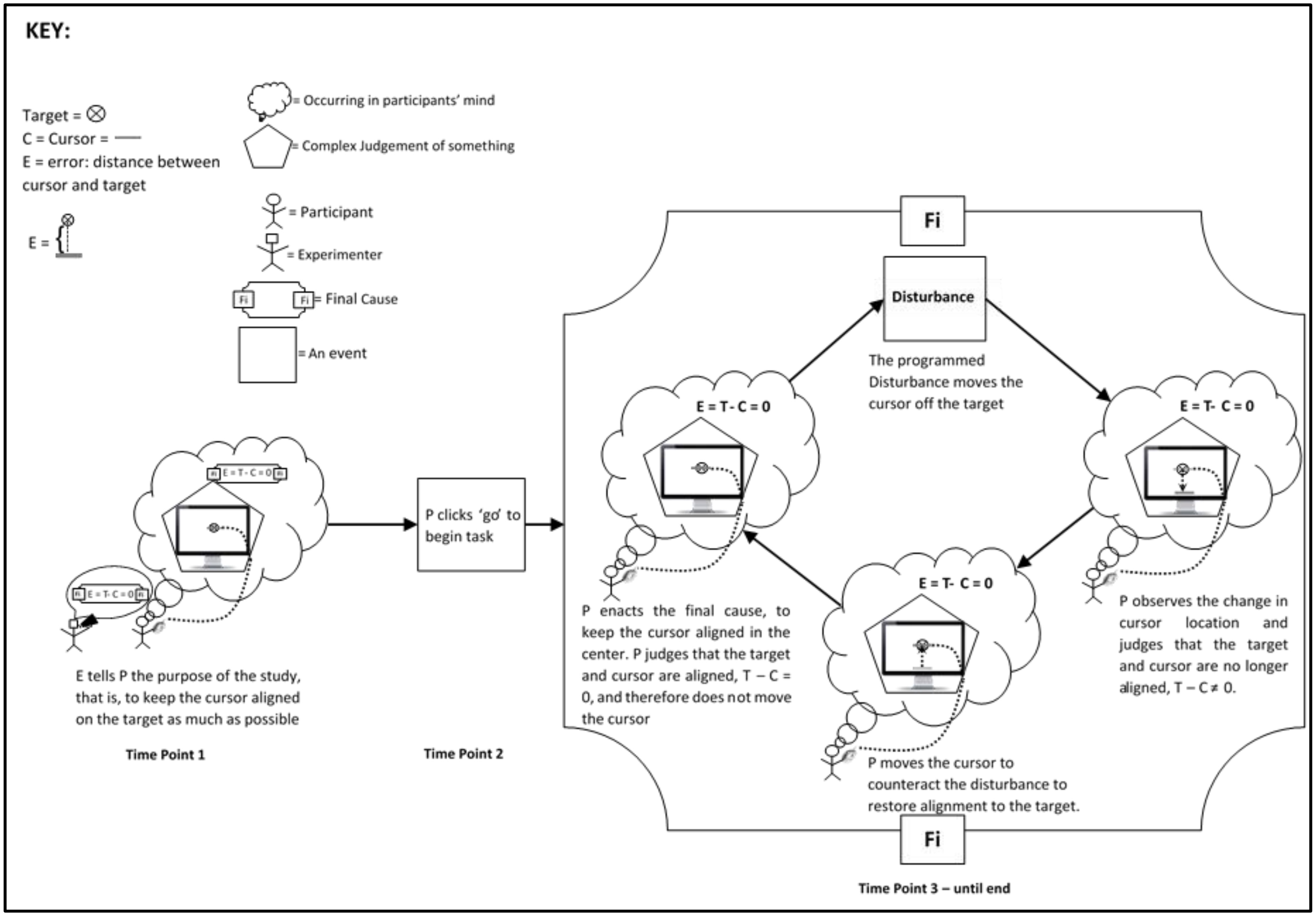
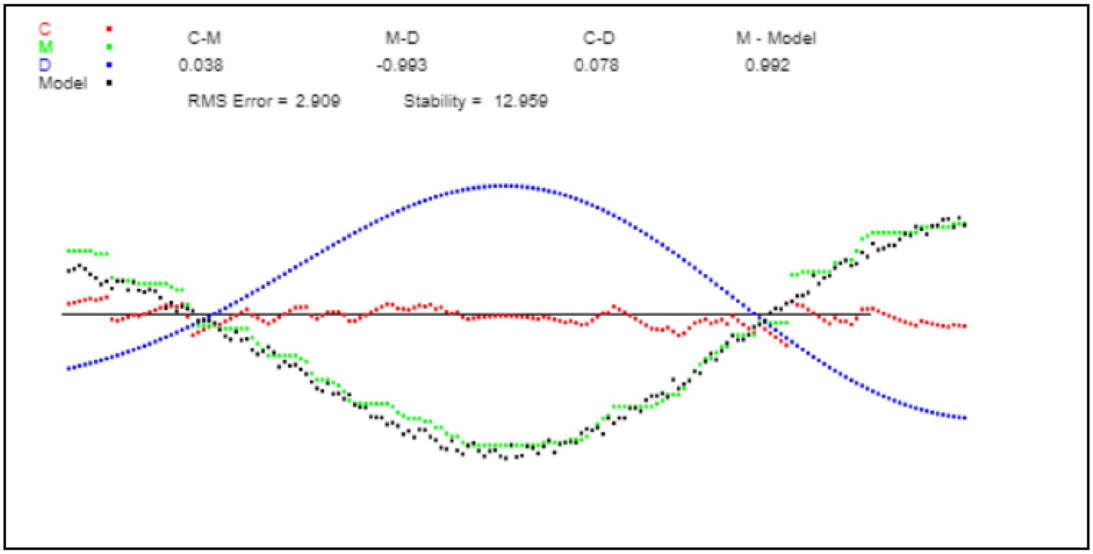


Figure 4

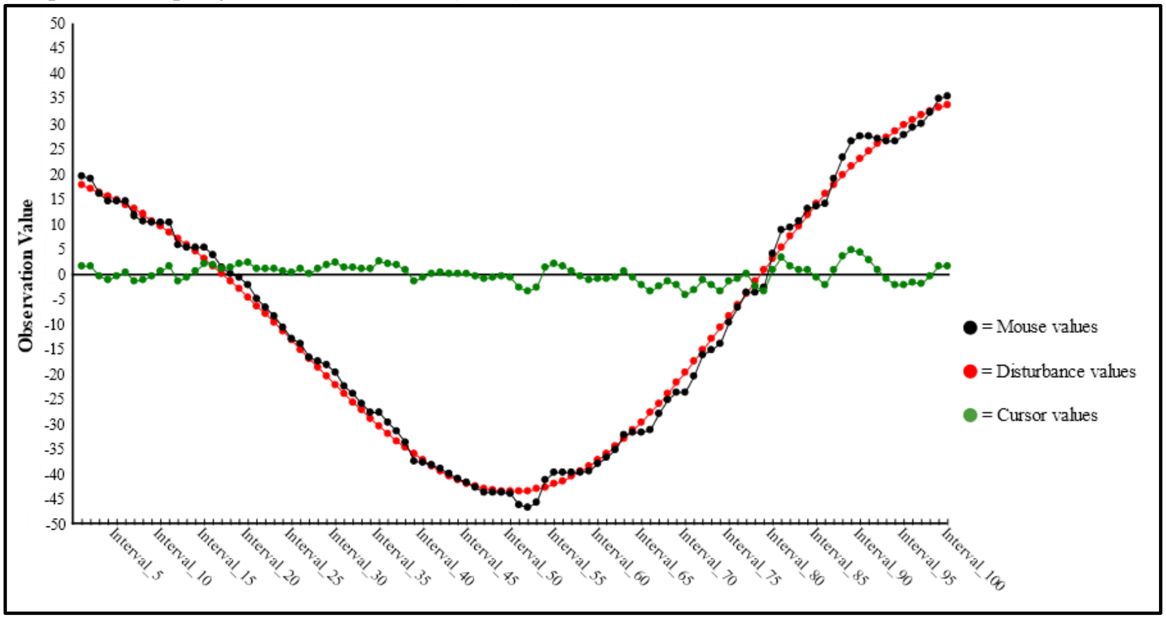
Example Output from the Nature of Control Task



Note. C represents the cursor position, M represents the mouse outputs/movements, and D represents the disturbances. C-M is the correlation between the cursor position and mouse outputs. M-D is the correlation between the mouse outputs and the disturbances. C-D is the correlation between the cursor and disturbances. RMS Error stands for Root-Mean-Squared Error, the closer to zero the greater the control exhibited. The larger the stability value, the more control the organism has exhibited over the cursor.

Figure 5

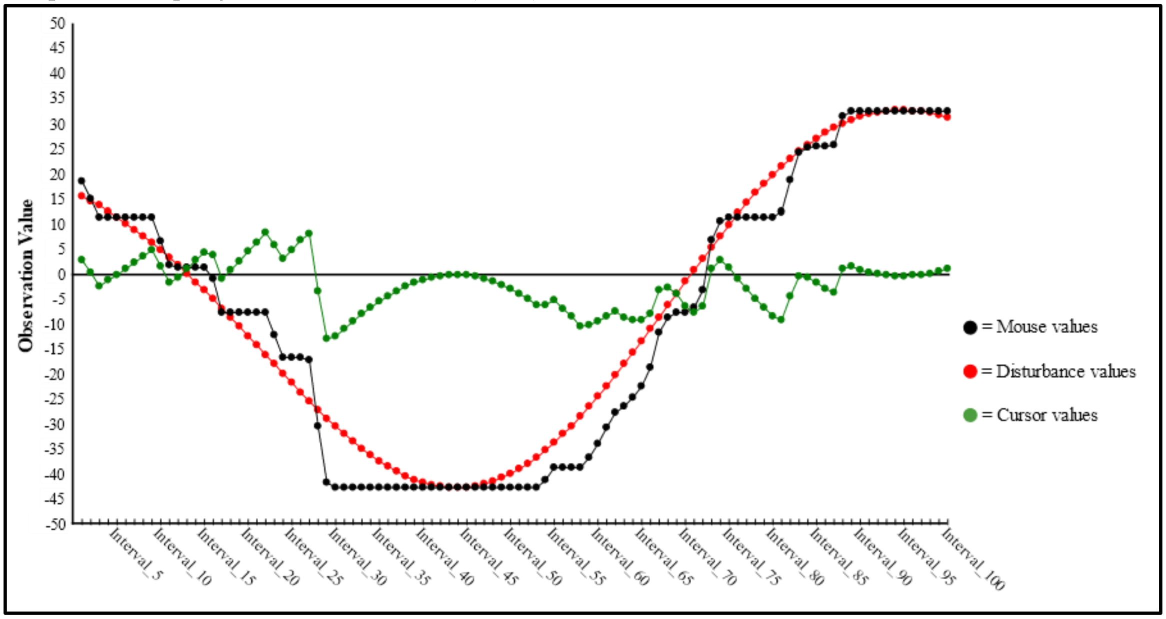
Graphical Output from the Best Case (Luke)



Note. Figure 5 is the output from the individual with the best run, Luke. This output occurred during Luke's test trial 2 run in the experiment. For visual demonstration purposes, every 10 data points were averaged into 1 data point to cut down from 1000 intervals to 100 intervals. Therefore, each interval in the current figures represents the average of 10 intervals from the actual task, which corresponds to the average of 160ms of tracking data.

Figure 6

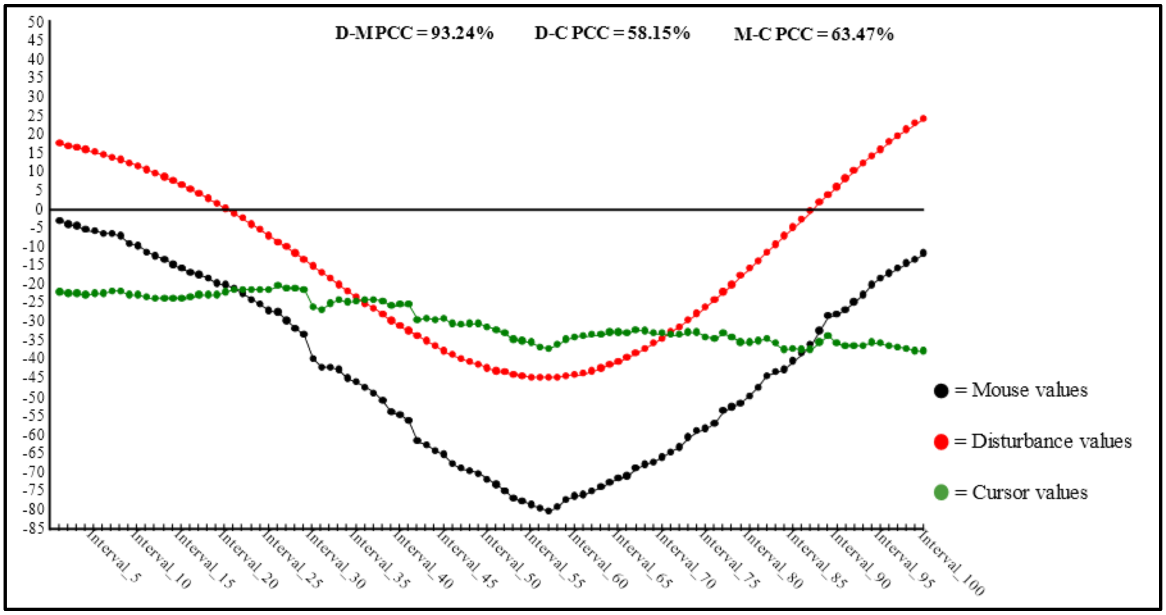
Graphical Output from the Worst Case (Ruth)



Note. Figure 6 is the output from the individual with the worst run, Ruth. This output occurred during Ruth's first run in the experiment. For visual demonstration purposes, every 10 data points were averaged into 1 data point to cut down from 1000 intervals to 100 intervals. Therefore, each interval in the current figures represents the average of 10 intervals from the actual task, which corresponds to the average of 160ms of tracking data.

Figure 7

Alternative Final Cause



Note. The current figure represents mock data in which the mouse was moved towards an alternative target or final cause (e.g., off and to the right of the target). The same visual averaging procedure used in Figures 5 and 6 was also used in the current figure.

Figure 8a

Randomized Movements Example 1

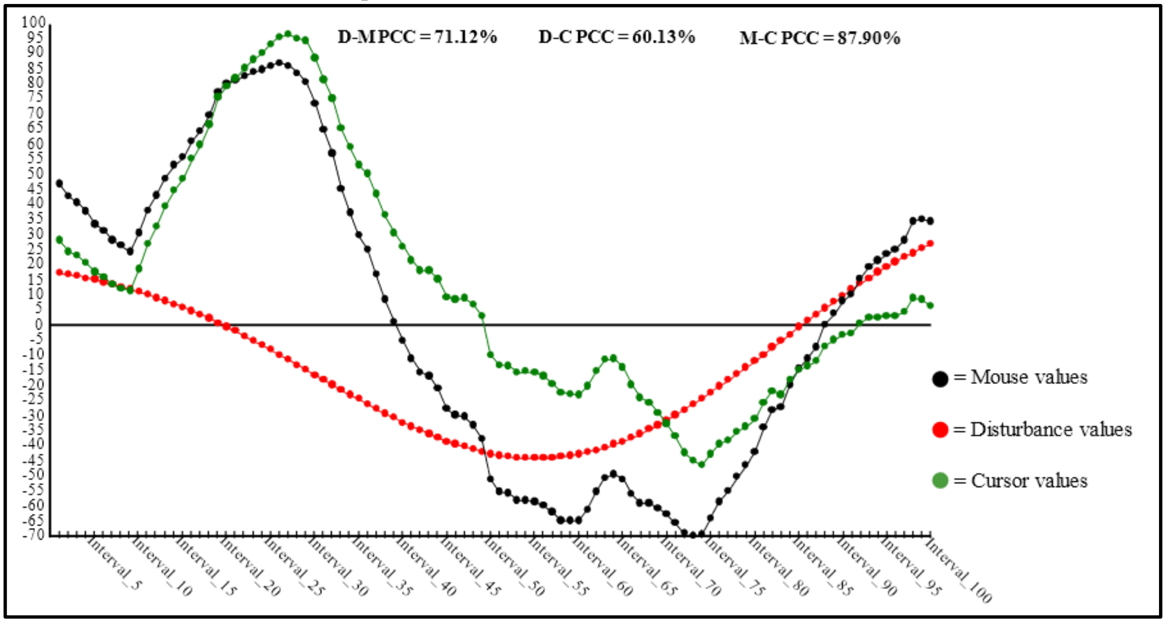
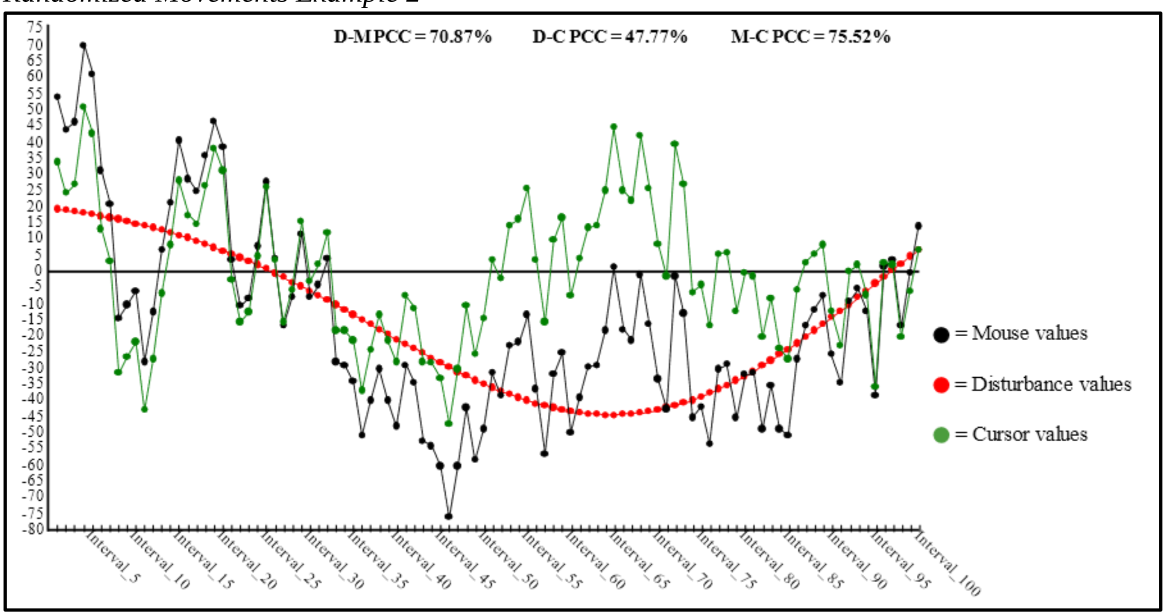


Figure 8b

Randomized Movements Example 2



Note. Figure 8a (top) and Figure 8b (bottom) represent mock data in which the mouse was moved randomly left or right with varied speeds. The same visual averaging procedure used in Figures 5 – 7 was also used in the current set of figures.

VITA

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