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SYSTEMATIC REVIEW

Automated Measures of Force and Motion Can Improve Our Understanding of Infants' Motor Persistence

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Every day, young learners are confronted with challenges. The degree to which they persist in overcoming those challenges, and the different ways they persist, provides critical insights into the various cognitive, motoric, and affective processes that drive behavior. Here, we present a systematic overview of the methodologies that have been traditionally used to study persistence, and offer suggestions for new approaches to the study of persistence that will make strides in moving the field forward. We argue that automated measures of force and motion, which have long been used in the study of infants' motoric behavior, can provide a means to unravel the psychological processes that guide infants' trying behavior. To illustrate this, we present a case study that highlights the novel lessons to be learned by the use of automated measures of force and motion regarding infants' persistence, along with an analysis of the benefits and drawbacks of this approach, as well as detailed instructions for application. In sum, we conclude that these measures, when used in conjunction with more traditional approaches, will provide creative new insights into the nature and development of early persistence.

***Keywords**:* automated behavioral analysis, cognitive development, infancy, learning, motor development, persistence

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Persistence, the act of working steadfastly to overcome challenges and achieve goals, has long been an important area of inquiry for researchers across disciplines. Scholars from education have been interested in persistence because it is a powerful measure of classroom engagement and a robust predictor of academic achievement (Duckworth & Gross, 2014; Duckworth, Peterson, Matthews, & Kelly, 2007). Developmental psychologists have examined persistence because it provides a window into what infants know about the world, and what they care about (Leonard, Lee, & Schulz, 2017; Lucca & Sommerville, 2018). Neuroscientists have investigated persistence as a way to gain unique insights into the reward circuitry of the brain (Gusnard et al., 2003). Persistence has been at the forefront of so many diverse areas of study because the construct is inherently interdisciplinary; it blends together key elements of cognition, affect, and motor behavior. To illustrate, imagine locking your keys inside a car. To get them out, you might draw on motor abilities and exert high levels of force in trying to pry the door open. You might recruit cognitive resources and contemplate the most strategic way to obtain the keys. As a consequence of the success or failure of your actions, you may grow frustrated, upset, or elated. Most likely, all of this is simultaneously occurring, highlighting that persistence is fundamentally tied up in different cognitive, motoric, and affective processes, making it an especially intriguing area of study. In the current paper, we argue that automated measures of behavior, particularly automated measures of force and motion, which have long been used in the study of motor development, can be applied to the study of persistence to unravel the psychological processes that guide infants' trying behavior.

To fully understand the nature of persistence, it is important to begin our investigations in infancy, because that is when individual differences in persistence first emerge (Messer et al., 1986). By examining early persistence, researchers can begin to gain a mechanistic understanding into how persistence develops, that is, the different factors that shape when and how it first emerges. In this review, we provide a systematic overview of how persistence has traditionally been examined during infancy. We then outline how new methodological approaches and advancements can further our understanding of persistence, with a specific focus on the use of automated measures of force and motion to measure persistence.

Background

Traditional Approaches to the Study of Persistence

Historically, researchers have examined infants' persistence by investigating problem-solving and exploratory behaviors in different contexts. To quantify trends in precisely how researchers have measured persistence in this work, we conducted a scoping meta-analysis (Tricco et al., 2016). A scoping meta-analysis is a research synthesis that investigates an exploratory research question by systematically identifying, acquiring, and synthesizing research on a topic (Colquhoun et al., 2014). Scoping meta-analyses are becoming increasingly prevalent as a means to provide a rigorous and transparent synthesis of the relevant literature in a particular field of study (Pham, Greig, Sargeant, & Mcewen, 2014). Here, we used this approach to document all the measures that researchers have used to assess persistence. Our initial approach was to gather publications examining behavioral persistence in children aged 0–36 months using Google Scholar and PsycINFO with the following search terms: persistence; infancy; toddlerhood; problem-solving; mastery motivation. We then selected articles that fit our criterion: the study must have examined children's persistence on a cognitive-based task. We further limited our search by excluding papers that examined perseveration (i.e., studies where the central task was designed to elicit a repetition of a particular response in the absence of a reward). After this initial search, we examined any relevant papers that met our selection criteria that were listed in the references of the selected articles. This search was conducted in October 2018.

Our meta-analysis revealed 37 manuscripts published between the years 1976–2018. An analysis of these papers revealed that researchers classified infants' persistence in one of five ways (Table 1): time spent on task (e.g., seconds spent trying to operate a toy; 38%), experimenter rating of persistence (e.g., rating of children's persistence in the face of difficulty on a 5-point scale ranging from refusal to engage with toy to active attempts to complete a challenging task; 16%), frequency of target behavior (e.g., number of times infants press a button to operate

Table 1 Proportion of Studies Investigating Persistence as a Function of Measurement Type

Category	% Studies	Authors (Year)
Time Spend on Task	38%	Belsky, Friedman, and Hsieh (2001), Bober, Humphry, Carswell, and Core (2001), Tamis-Lemonda, Bornstien, and Baumwell (2001), Caplan and Kinsbourne (1976), Frodi, Bridges, and Grolnick (1985), Grolnick, Frodi, and Bridgers (1984), Hauser-Cram (1996), Maslin-Cole, Bretherton, and Morgan (1993), Messer et al. (1986), Redding et al. (1988), Wachs (1987), Yarrow et al. (1982, 1983, 1984)
Experimenter Rating of Persistence	16%	Atun-Einy, Berger, and Scher (2013), Kelley, Brownell, and Campbell (2000), Martin, Ryan, and Brooks-Funn (2013), Oppenheimer (2011), Schieche and Spangler (2005), Wang et al. (2017)
Frequency of Target Behavior	16%	Fagot, Gaucian, and Kavangh (1996), Golinkoff (1986), Leonard et al. (2017), Lucca and Wilbourn (2019), Matas, Arend, and Sroufe (1978), Redding et al. (1990)
Parental Report of Persistence	11%	Pipp-Siegal et al. (2000), Sparks, Hunter, Backman, Morgan, and Ross (2012), Sullivan and Comody (2018), Wang, Hwang, Liao, Chen, and Hseih (2011)
Multiple Measures	19%	Banerjee and Tamis-LeMonda (2007), Frankel and Bates (1990), Glenn, Dayus, Cunningham, and Horgan (2001), Jennings, Harmon, Morgan, Gaiter, and Yarrow (1979), Lewis, Sullivan, and Kim (2015), McCarty, Clifton, and Collard (1999), Sullivan and Comody (2018)

a toy; 16% of studies), parental report of persistence (e.g., dimensions of mastery questionnaire, which includes questions such as, "will work for a long time trying to do something hard"; 11%), or a combination of at least two of the other measures (e.g., time spent persisting and parental report; 19%). This review also revealed that researchers tend to use a specific subset of tasks when measuring persistence that can be classified in six general categories: cause-and-effect/means-end toys, puzzles or shape sorters, standardized assessments, questionnaires, tools/utensils, or dyadic social interactions (Table 2). These tasks tend to be chosen because they are either difficult or impossible for infants and toddlers to solve.

Each of these methods has unique advantages and has revealed important insights into the nature of early persistence: these measures have uncovered that persistence is a relatively stable construct across development, and predicts broader cognitive abilities such as problem-solving performance (Yarrow, Morgan, Jennings, Harmon, & Gaiter, 1982). Moreover, these measures have led researchers to discover that individual differences in persistence emerge in the first half of infants' first year (Messer et al., 1986), which are shaped by different parenting styles (Banerjee & Tamis-LeMonda, 2007; Lucca, Horton, & Sommerville, 2019). However, there are methodological limitations to each of these measures, particularly in terms of their ability to fully and accurately assess infants' persistence.

In examining the *frequency of target behavior,* researchers are able to provide a discrete count of how often a specific behavior of interest occurred. However, a shortcoming of this approach is operationalizing how behaviors are parsed and codified. That is, how do researchers compare an infant who produced a target behavior once, but for a long period of time, to an infant who produced a target behavior many times, but for short periods of time? The *time infants spend on a task* is a common metric of persistence because it is quick and easy to code. However, this measure often misses the richness and complexity that is associated with infants' actual behavior in the task. Two infants may spend the exact same amount of time trying, but one infant may utilize a more adaptive strategy than the other. In this scenario, if researchers had only examined the duration of trying time, they would have overlooked an important dimension of infants' behavior. Another measurement type, *experimenters' rating of persistence*, avoids some of these pitfalls because it is a more global measure. In rating trying behavior, researchers can take into consideration both the amount of time infants spent trying, as well as

Table 2 Range of Tasks Used to Measure Early Persistence

Task	Example Papers
Cause and effect/Means-end toys	Hauser-Cram (1996), Yarrow et al. (1982)
Puzzles or shape sorters	Frankel and Bates (1990), Redding et al. (1988)
Standardized Assessments (e.g., Bayley Scales of Infant and Toddler Development)	Martin et al. (2013), Messer et al. (1986)
Questionnaire	Sparks et al. (2012)
Tools or utensils	Bober et al. (2001), McCarty et al. (1999)
Social interaction	Golinkoff (1986), Lucca and Wilbourn (2019)

the specific behaviors infants deployed while trying, in calculating their persistence rating. Thus, researchers can also simultaneously integrate non-specific information that can be difficult to quantify (e.g., affective responses, vocalizations). However, this measure can be problematic in that it is inherently subjective (potentially resulting in low inter-rater reliability). These drawbacks make it difficult to standardize ratings within a study (e.g., to identify precisely the range and nature of behaviors that are considered across participants and across different raters), as well as across different studies. *Parental report*, another widely used measure of persistence, can also provide a more global and representative assessment of infants' overall persistence. However, as with experimenter rating, parental reports can be highly biased and vary greatly across participants.

A Multi-Faceted Approach to Studying Persistence

These examples highlight that persistence is a multi-faceted construct. Thus, to fully understand early persistence, it is critical to utilize multiple measures that provide a rich and detailed representation of persistence. For example, an infant who is working hard while displaying positive affect may hold the expectation that the task *should* be hard, and is therefore not frustrated, and be more persistent in future endeavors. An infant who is working hard while displaying negative affect may have expected the task to be easy, and when it wasn't (i.e., when their expectations were violated), grew upset. This infant may be quicker to give up trying, and less likely to try in the future. This example highlights that using multiple measures when examining persistence can provide important insights the underlying processes driving the behavior, and may also be useful for predicting future behavior.

Use of Automated Behavioral Analysis Techniques in Infancy Research

Automated behavioral analysis techniques, such as automated measures of force and motion, can provide researchers with a powerful, additional tool to study persistence. These measures have long been used in infancy research (Robin, Berthier, & Clifton, 1996; Thelen, Corbetta, & Spencer, 1996; Thelen, Ulrich, & Niles, 1987; Von Hofsten & Rosander, 1997). Beginning in the 1980s and extending into the present day, researchers have used automated behavioral analysis techniques to provide novel insights into the development of difficult and complex motoric behaviors during infancy (e.g., walking, kicking, motor coordination; Bril, Dupuy, Dietrich, & Corbetta, 2015; Fetters, Sapir, Chen, Kubo, & Tronick, 2010; Snapp-Childs & Corbetta, 2009). Automated measures of force and motion offer a powerful way to study micro-level behaviors because they provide high-resolution, fine-grained, and standardized measures of behavior. These techniques have led to critical scientific breakthroughs in infant motor development. For example, in an experiment conducted by Thelen et al. (1987), a 3D motion analysis of 7-month-olds' leg movements on a treadmill revealed that interlimb coordination is a core component of infants' motor ability that is not only present early in ontogeny, but is also already quite established from the outset. More recently, these measures have been used to investigate a suite of cognitive abilities: ranging from motor memory (Diedrich, Thelen, Smith, & Corbetta, 2000), to tool use abilities (Kahrs, Jung, & Lockman, 2014) to infants' understanding of object affordances (e.g., use of force in understanding weight perception; Kahrs, Jung, & Lockman, 2013; Lockman & Kahrs, 2017). However, the field has yet to capitalize on these metrics to study more *complex* and *abstract* psychological processes, such as advanced reasoning abilities and metacognition, which are critical drivers of early persistence (Lucca & Sommerville, 2018).

Automated Measures of Force and Motion Can Provide New Insights Into Persistence

Here, we make the case that automated measures of force and motion, when used in conjunction with the traditionally utilized measures outlined above, can more precisely delineate the construct of persistence. Though there are many potential tools that may enrich the study of persistence, here, we focus specifically on automated measures of force and motion because (1) new computational and technological advances make these automated measures more affordable and accessible than ever before, (2) we recently started employing these measures in our lab and have new insights to share, and (3) these measures focus on the motoric aspects of behavior, the theme of this special issue.

Now is an exciting time for researchers to integrate these measures into the study of infants' persistence in particular because recent technological advances have made them more adaptable to infant-based behavioral research. That is, they are small enough to be implemented in infant tasks, and new developments in markerless tracking makes 3D motion capture much more feasible for use with infants – placing physical markers on infants, as was necessary with older 3D motion tracking systems, is problematic because it is difficult to get markers in place on infants, and once in place, they are often distracting and thereby disrupt naturalistic behavior. And finally, the hardware required to measure force and motion are less expensive and easier to purchase than when these measures were first implemented in infancy research (e.g., they are available off the shelf through Amazon as opposed to only through special vendors; see Supplemental Materials [available online]). See Table 3 for an overview. Though these measures are not completely novel, the case we present here is that they are new in their application of studying infants' persistence and the cognitive processes that drive it (e.g., complex decision making, planning).

New Low-cost Depth Cameras Expand State-of-the-art 3D Motion Capture

While 3-dimensional human motion has been acquired and analyzed for decades (Aggarwal & Cai, 1999), recent developments in low-cost depth cameras, such as the Intel RealSense and the Microsoft Kinect, extend high-precision 3D motion capture beyond relatively complex and expensive multi-camera tracking systems to more simplified and portable single device configurations. This allows researchers to perform sophisticated motion analysis in non-specialized settings. These new systems have high levels of accuracy (Carfagni et al., 2019) making them useful for clinical applications involving metrics such as gait analysis (Bower

Table 3 Description of Automated Force and Motion Measures

Measure	Description	Technical Specifications
Force	To measure infants' force, a force sensor is embedded in a target location (e.g., inside a toy). The force sensor is connected to a computer which emits a reading of force at .01 second intervals in pounds per square inch (PSI). There are open-source software programs available online that will read and store force measurements (e.g., Micro-Measurements MM01 MultiDAQ). In between readings, it is important to zero out the force reading so no residual force carries over to the next trial and/or participant.	**Hardware:** Force sensor **Software:** Micro-Measurements MM01 MultiDAQ **Output**: Force in pounds per square inch
Motion	Measurements of 3-dimensional movement are acquired using a newly developed line of Intel RealSense depth cameras (400 series). Through on-chip algorithms for stereo-matching as well as active infrared scanning (invisible to humans) these cameras are capable of dense 3-dimensional reconstruction of the entire experimental setup and participant. Both color video and depth data are acquired at up at up to 90 frames per second.	**Hardware**: Intel RealSense 400 series depth cameras **Software**: *Acquisition*: Intel RealSense open source software development kit (SDK) *Data processing*: Matlab (Mathworks) **Output**: XYZ coordinates of motion.

et al., 2019; Clark, Mentiplay, Hough, & Pua, 2019). Increasingly, researchers in human movement analysis are turning to these simplified, low-cost options to expand the scope of clinical outcome measures and obtain data from patient populations that would be unable to be assessed using a lab-installed system (Siena, Byrom, Watts, & Breedon, 2018). Indeed, in one recent study, measures for spasticity in patient movement obtained from a clinical standard Optitrack three-dimensional motion analysis (3DMA) system were well-replicated by measures taken from a single Microsoft Kinect 3D camera (Banky et al., 2019). These studies indicate that single camera 3D motion capture technology has now matured to the point that these cameras can be used to obtain high quality data as validated against the standard clinical practice for 3D human motion analysis. Additionally, open source software (such as that found at http://3dtracker.org/) now provides user guides and pre-written code to run motion acquisition with these new 3D cameras.

Markerless Motion Capture

Markerless motion capture is at the forefront of human motion analysis (Colyer, Evans, Cosker, & Salo, 2018; Insafutdinov, Pishchulin, Andres, Andriluka, & Schiele, 2016) as well as comparative work across a variety of species (Mathis et al., 2018). Markerless motion capture has many advantages over traditional, marker-based approaches, including the ability to unobtrusively monitor motion from more natural movements than those that may be possible with a marker-based system. This technology has recently been adapted for use in videos from 8-17 week old infants to monitor for cerebral palsy (Marchi et al., 2019). However, these advantages must be weighed against possible inaccuracies in motion estimation as well as the difficulty of employing the software available to enact these newly developed deep learning approaches.

A key question regarding markerless motion capture is whether one sacrifices accuracy for experimental convenience by not using a marker-based system. In side-by-side comparisons, modern approaches to markerless motion capture perform relatively well (Schmitz et al., 2015); however, these approaches are often computationally intensive and require specialized analysis software (Colyer et al., 2018).

Adapting this technology can be aided by the large open source movement behind it, including resource such as code available at Github software repositories, including user guides and test data (e.g., https://github.com/AlexEMG/DeepLabCut). Although the software is freely available and can be run across multiple operating systems (Nath et al., 2018), some key limitations remain. These include the need to install specialized, open source software such as TensorFlow (Abadi et al., 2016) and the Python 3 programming language as well as recommendations to use modern GPUs in order to train the deep learning networks in a reasonable amount of time (Mathis & Warren, 2018). Additionally, as for all deep-learning based approaches, one must hand-annotate a small subset of data in order to provide a training data set for the algorithm. With modern approaches, this training data set has shrunk and strong performance across hours of video can be obtained after hand-labeling only 100-200 frames of data (Mathis et al., 2018).

New Tools for Studying Persistence

Given that infants' trying behaviors are most frequently manifested during motor activity, automated measures of force and motion can provide valuable and objective indices of infants' trying behavior that have not previously been utilized, thereby allowing researchers to assess infants' persistence with higher accuracy and resolution than ever before. By using these techniques, researchers can access more quantifiable data for a construct that is otherwise difficult to measure. By using automated measures of force and motion, researchers can go beyond binary measures of infants' trying behavior, to provide more rich, graded, and detailed assessments of trying. In this way, these measures will provide a more nuanced lens for understanding persistence, help researchers more precisely delineate the construct of persistence, and reveal which features of early persistence are most predictive of later learning outcomes

Using Automated Measures of Force and Motion to Study Persistence: A Case Study

In what follows, we present a case study from our lab that highlights how automated measures of force and motion can be used to better elucidate infants' trying behaviors. In this study, we measured infants' trying behavior by presenting them with an out-of-reach toy within a container that was only accessible by pulling a rope attached to the container.[1] The task was impossible, such that no matter how hard they pulled the rope they could not get the toy (because, unbeknownst to infants, the container housing the toy was glued to the table top). We installed a force gauge inside the toy that measured the force infants exerted in their pulling behavior, and we installed a 3D motion tracker system (Intel RealSense depth camera; capabilities tested by Carfagni et al., 2019) in the room that detected infants' motion trajectory by following a predefined color in the environment (here, we used a blue handle on the rope Figure 1). See the Supplemental Materials [available online] for a full description of the hardware and software used to generate, extract, and analyze this data.

The goal of our case study was to begin to elucidate three questions pertaining to early persistence (Table 4): (1) to what extent is persistence distinct from other closely related constructs? (2) to what degree do different dimensions of persistence hang together? and (3) what is the predictive power of early persistence?

A key question in the literature on early persistence is whether persistence per se is an independent construct worthy of study, or whether it is simply a feature of other closely related constructs, such as temperament. The degree to which these constructs overlap, or are distinct from each other, is an empirical question that can be answered using automated measures of force and motion to study persistence. For example, automated measures of force can help researchers identify whether there are distinct profiles of trying behaviors, and whether these profiles map onto traditional measures of temperament. It has been argued that two measures are redundant if there is a high degree of overlap (i.e., correlation coefficient between the two is above .70; Mcgillivray & White, 1993). Thus, if persistence and temperament account for high degrees of shared variance, it is likely not worth treating them separately.

Profiles of trying can be characterized by the degree of force infants apply while trying, and how this behavior varies over time. Degrees of force can be computed by calculating the magnitude of the maximum force (measured in pounds per square inch) infants exerted during the task, and change in force over time can be computed by examining the rate of change in force from the first to final

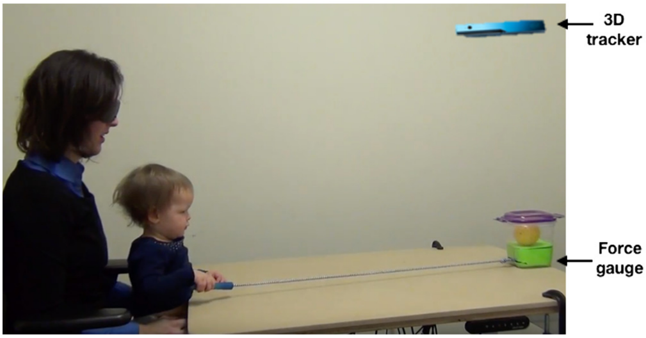

Figure 1 — Room set up and location of automated measures of force and motion.

Table 4 Using Automated Measures of Force and Motion to Elucidate Key Open Questions Surrounding Early Persistence

Question	Approach	Implications
To what extent is persistence distinct from other related constructs (e.g., temperament)?	Test whether infants can be categorized into distinct profiles of trying behaviors based on patterns of trying force (e.g., magnitude and timing of force), and examine whether these profiles map on to traditional measure of temperament.	Delineating persistence as a distinct construct from temperament is critical because it will provide important insights into the malleability of persistence, as well as help inform important debates about related constructs (e.g., grit) that emerge later in development.
To what degree do different dimensions of persistence hang together?	Assess whether there are high degrees of overlap across different automated measures of behavior, such as force and motion (e.g., is an infant who tries hard, also one who is more likely to try in more varied ways?).	By creating and classifying infants into these different force and motion 'profiles' we can learn more about the nature of their trying behavior as well as their task representations.
What is the predictive power of early persistence?	Measure different features of trying behaviors (e.g., latency of deploy maximum effort, more time persisting, more effortful persisting) and examine which feature is most predictive of later learning outcomes.	This approach offers a powerful new way to predict later learning outcomes, as it may more accurately and robustly capture infants' persistence.

block of the trial and/or experiment. In the rope pulling example described above, infants may be *slow to warm up or cautious* in their trying behavior, which would be characterized by low levels of force combined with a constant or slow increase in force over time. Infants may be characterized as *active or feisty* if they are erratic and unpredictable in their trying profiles: these infants may grow easily upset and demonstrate initially high levels of force, but dramatically decline their levels of force across the duration of the experiment. Their individual tries may also be more impulsive, and characterized by short bursts or yanks on the rope (characterized by shorter peak durations).[2] Infants who are *easy or flexible* may engage in more adaptive trying behaviors; they may apply generally high levels of force, ramp up their trying over time, and have longer peak durations, which are reflective of more thoughtful, prolonged, and deliberate trying behaviors. See Figure 2 for examples.

Understanding whether persistence can explain additional variance in later developmental outcomes, above and beyond temperament, is critical because temperament is a relatively fixed trait (Strelau & Zawadzki, 1995), whereas persistence may be more malleable and susceptible to influence from the social environment (Grolnick et al., 1984; Leonard et al., 2017; Lucca et al., 2019). Revealing the degree to which these constructs overlap also has the potential to

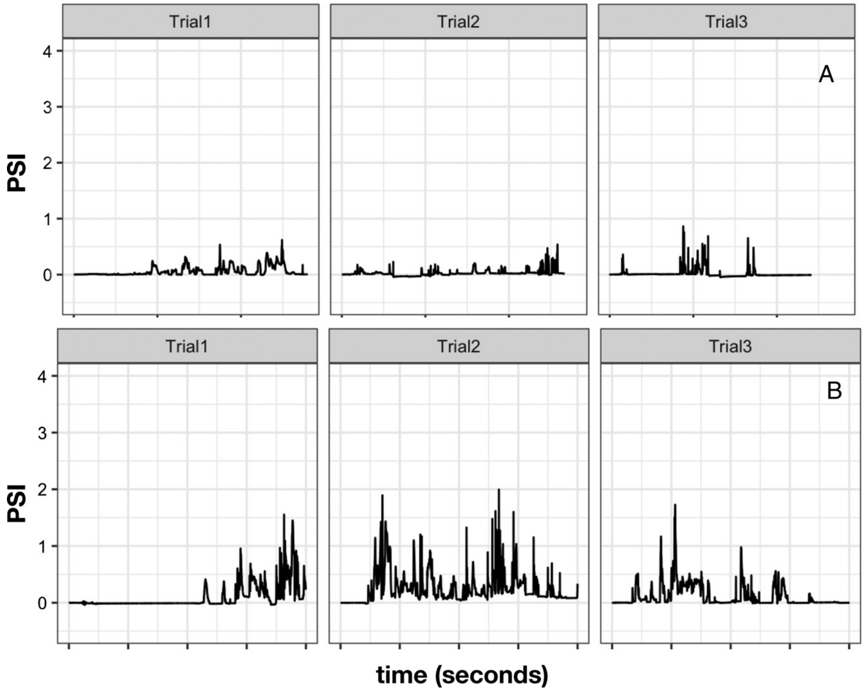

Figure 2 — Infants' trying force, measured in pounds per square inch, mapped over time. The top graph (A) is time-course data from a single infant who exhibited low levels of trying across three trials of an experiment, the bottom graph (B) is time-course data from a single infant who exhibited high levels of trying across the three trials of the experiment.

provide important insights into the nature of related constructs later in life, such as "grit", which is often the subject of debate in terms of whether it is a unique construct (that reflects perseverance and consistency of interests) or a rebranding of personality traits (i.e., consciousness; for an overview see Credé et al., 2017).

Another key question surrounding early persistence concerns the degree to which different dimensions of trying behavior hang together. Automated measures of force and motion can help answer this question by examining the extent to which there are high degrees of overlap across different types of trying behavior. To measure this, infants can be classified into four different force-motion profiles that vary along two dimensions: (1) how much force infants apply in their trying behavior (with increased force representing more intense trying behavior), and (2) how much spatial variability infants display while trying (with increased spatial trajectories representing more varied, distinct modes of trying).[3] Spatial variability in trying behavior can be computed by calculating the degree of variability in infants' X, Y, and Z coordinates of movement (see Figure 3 for examples of high vs. low degrees of spatial variability in trying behaviors). Infants who score high on force and motion engage in the highest levels of targeted trying behavior, and

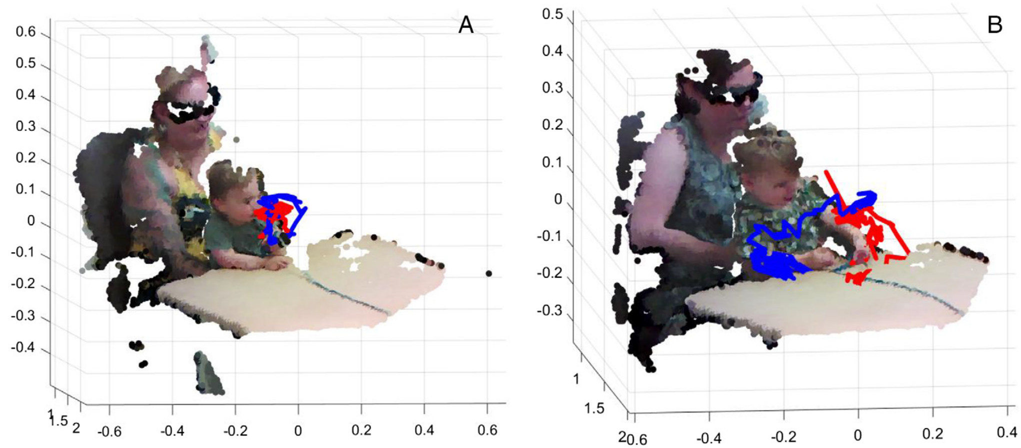

Figure 3 — Infants' trying behavior as manifested through 3D movement analysis. Each colored line (blue and red) represent a single rope-pulling behavior. An example participant who demonstrated low levels of spatial variability in their pulling behavior (left) is contrasted with an infant who demonstrated high levels of spatial variability in their pulling behavior (right).

deployed the most diverse strategies, as demonstrated by heightened force applied from distinct angles. Infants who score high on force but low on motion also engage in targeted trying, but tend to stick to a single trying strategy; as their low spatial variability indicates they were not trying in multiple distinct ways. Infants who score low on force, but high in motion can be classified as more exploratory in their actions. These infants may be trying, but in a way that is more exploratory and investigative than infants who are applying high levels of force, or in a way that is perseverative in nature (Diedrich et al., 2000). And finally, infants who score low on force and motion may simply be disinterested in the task at hand. By creating and classifying infants into these different force and motion 'profiles' we can learn more about the degree to which different dimensions of trying hang together. This approach can be utilized across the lifespan as the complexity of persistence deepens: for example, it can be used to measure the degree to which different dimensions of persistence (cognitive persistence vs. motor persistence) overlap or are distinct.

A final critical open question in the literature surrounds the precise predictive power of early persistence. That is, which features of early persistence are most predictive of later learning outcomes? One possibility is that sheer persistence is most predictive of later learning outcomes; infants who try for longer when given a difficult to solve task will have better learning outcomes than infants who tend to persist less. An alternative possibility is that the degree to which infants engage in deliberate and planned persistence is the most powerful predictor of later learning outcomes. Automated measures of force can disentangle these possibilities. For example, automated measures of force can provide precise information about infants' latency to exert their highest levels of physical effort. A slower latency to exert one's maximum effort may be more reflective of deliberate and cognitively complex trying acts. This delay-to-act has been seen in other more basic motoric behaviors during infancy: as early as 10 months, infants are slower to perform an action that requires more precision and control than one that is easier to execute (i.e., fitting a ball down a tube vs. throwing a ball; Claxton, Keen, & McCarty, 2003). This delay-to-act reflects a sophisticated and deliberate planning process that is driven by the complexity of the physical act. Whether infants demonstrate this level of sophistication in their motor planning as a function of their *representations* of a task difficulty—as opposed to *sheer* difficulty—can be examined through infants' persistence. For instance, in the rope-pulling example provided above, all infants are faced with an impossible task to solve. However, some infants have evidence that the task should be difficult, whereas others have evidence that the task should be easy. When infants expect the task to be hard, they are slower to apply their maximum physical force on the task than when they expect the task to be easy, in which case they are quicker to exert their maximum force. This example highlights that infants engage in sophisticated levels of planning that go one step further than simply reasoning about the concrete, physical features of a task. Rather, infants engage in a high-level, sophisticated planning process that is driven by their abstract representations of a task's difficulty. What's more, researchers can use this information to predict infants' later persistence to determine which features of early persistence (e.g., more planning, more time persisting, more effortful persisting) are most predictive of later learning outcomes.

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The Utility of Automated Force and Motion Measures Across Ages, Contexts, and Species

Automated measures of force and motion provide particular promise in moving developmental researchers beyond binary outcomes since they provide graded, fine-grained, continuous information about infants' preferences, or how much they know about something. For example, experiments designed to probe the nature of infants' social preferences will measure whether infants prefer one agent (e.g., a prosocial agent) over another (e.g., antisocial) agent (Hamlin, Wynn, & Bloom, 2007). Automated measures of force and motion can be leveraged here to provide additional information about the strength of infants' preferences, or their rank ordering of different agents along a continuum of prosociality. Infants could be presented with agents of varying levels of prosociality, and researchers could measure whether the degree to which infants exert physical effort in the service of interacting with those agents (e.g., the amount of force they will exert to obtain an agent who is stuck to a board) increases as a function of the prosociality of the agent, to provide richer information about the nature of infants' preferences.

In addition to providing new insights across domains of higher-order reasoning, these measures are ideally suited for conducting comparative research because they can be applied across diverse contexts, species, and ages. Researchers can use these measures to answer questions about age-related changes in different abilities, since these metrics translate well across ages. Moreover, these measures can also be used to conduct cross-species comparisons. Precise motion tracking can be used to examine cross-species differences in social behavior (Matsumoto et al., 2013), decision-making and navigation strategies (Ben-shaul, 2017; Matsumoto, Uehara, Urakawa, & Takamura, 2014; Nakamura et al., 2016), including how different species make sense of complex information to decide when and how to act (e.g., combining odor information with wind information to localize a new food source; Baker et al., 2018; Gire, Kapoor, Arrighi-Allisan, Seminara, & Murthy, 2016). Additionally, these metrics can be combined with computational modeling to discover fine-scale organization of behavior that eludes observer-based scoring methods (Wiltschko et al., 2015).

Finally, recent advances in computer vision using deep convolutional neural networks have resulted in a watershed moment for complex motion analysis across species. These approaches now support automated human pose analysis across multiple subjects at once (e.g., identifying distinct body parts across groups of individuals; Insafutdinov et al., 2016) as well as more user-friendly implementations for use across species in the lab (Mathis et al., 2018). Since these techniques use 2D images as input, they can be used with the color images generated by cameras such as the RealSense. This 2D segmentation could then be mapped onto the simultaneously acquired depth image to provide automated 3D pose estimation with limited changes to existing algorithmic approaches. Supporting this approach for automated 3D pose estimation, current state-of-the-art developments in this area are based on open-source software and can thus be adapted to specific use cases.

Challenges and Potential Hurdles

With all of the advantages of using these measures, there also come some drawbacks. First, there is a steeper learning curve if you are not familiar with the technology. While automated measures of force are relatively easy to implement and extract data from, automated measures of motion are drastically more involved in that they require more intensive programming to extract and process data. Though once familiar with these methods, implementation is fast and easy since the data extraction process can be automated, as opposed to relying on human coders. Second, depending on what is being measured, it is important that these metrics are integrated with other metrics (e.g., human observation coding). For example, in the rope-pulling example highlighted above, a child may have high degrees of spatial variability and strong force metrics, but if they perform these actions in the service of simply playing with the rope (as opposed to goal-directed pulling to obtain the out-of-reach toy) they would not be meaningful. Thus, we recommend that these tools be used in conjunction with other well-validated measures of infant behavior.

Summary and Conclusions

In sum, we have argued for taking into account a battery of measures when measuring infants' behaviors. Specifically, we've reviewed two tools that will be useful to add to the battery of measures that researchers use to study persistence: automated measures of force and automated measures of motion. The clear advantages that stem from using these measures include: increased ability to clearly quantify variables of interest that are often difficult (or impossible) to measure via direct observation, and though there might be a steep learning curve involved in initially using these measures, they are efficient data collection tools once they are up and running. These measures provide promise not only for further elucidating early persistence and individual differences in developmental change, but they can also be used to study persistence on a larger timescale and across species, and provide creative new insights into other domains of learning as well.

Notes

1. The participants described here are from a larger study investigating infants' social cognitive development (Lucca, Horton, & Sommerville, n.d.). We received institutional approval to conduct this research, and the informed consent was provided by infants' caregivers to participate in this study and have their images shared.

2. A "peak" in raw data can be extracted using the *peaks* function of the IDPmisc package in R (Locher & Ruckstuhl, 2012). A default minimum peak height is set by the function as 1/10th of the maximum peak for a given individual trial. To eliminate peaks detected by sheer noise, we set a minimum peak threshold using the following parameters: in a given peak, force must last longer at least 300 ms and reach a minimum of .5 pounds per square inch.

3. These profiles can be generated with the following steps. Once force and motion data are collected, infants can be classified in one of these four categories through a *k* means cluster analysis. Infants' standardized force score (a composite of the force metrics described above, i.e., maximum force applied, number of peaks, average width of peaks, time spent applying force) and standardized spatial variability score (the degree of spatial variability displayed across the duration of the experiment) can be entered into the analysis. Once infants are classified into one of the four clusters, a multinomial regression can be used to test whether a factor of interest (e.g., experimental condition) can predict group membership.

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References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., . . . Google Brain. (2016). TensorFlow: A system for large-scale machine learning. In *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI)* (pp. 265–283).

Aggarwal, J.K., & Cai, Q. (1999). Human motion analysis: a review. *IEEE Nonrigid and Articulated Motion Workshop, 73*(3), 90–102. doi:10.1109/NAMW.1997.609859

Atun-Einy, O., Berger, S.E., & Scher, A. (2013). Assessing motivation to move and its relationship to motor development in infancy. *Infant Behavior and Development, 36*(3), 457–469. PubMed ID: 23659823 doi:10.1016/j.infbeh.2013.03.006

Baker, K.L., Dickinson, M., Findley, T.M., Gire, D.H., Louis, X., Suver, X.M.P., . . . Haven, N. (2018). Algorithms for olfactory search across species. *The Journal of Neuroscience, 38*(44), 9383–9389. PubMed ID: 30381430 doi:10.1523/JNEUROSCI.1668-18.2018

Banerjee, P.N., & Tamis-LeMonda, C.S. (2007). Infants' persistence and mothers' teaching as predictors of toddlers' cognitive development. *Infant Behavior and Development, 30*(3), 479–491. PubMed ID: 17683756 doi:10.1016/j.infbeh.2006.12.001

Banky, M., Clark, R.A., Mentiplay, B.F., Olver, J.H., Kahn, M.B., & Williams, G. (2019). Toward accurate clinical spasticity assessment: Validation of movement speed and joint angle assessments using Smartphones and camera tracking. *Archives of Physical Medicine and Rehabilitation. 100*(8), 1482–1491. PubMed ID: 30684484 doi:10.1016/j.apmr.2018.11.026

Belsky, J., Friedman, S.L., & Hsieh, K.H. (2001). Testing a core emotion-regulation prediction: does early attentional persistence moderate the effect of infant negative emotionality on later development? *Child Development, 72*(1), 123–133. PubMed ID: 11280474 doi:10.1111/1467-8624.00269

Ben-shaul, Y. (2017). OptiMouse: A comprehensive open source program for reliable detection and analysis of mouse body and nose positions. *BMC Biology, 15*(1), 41. PubMed ID: 28506280 doi:10.1186/s12915-017-0377-3

Bober, S.J., Humphry, R., Carswell, W., & Core, A.J. (2001). Toddlers' persistence in the emerging occupations of functional play and self-feeding. *The American Journal of Occupational Therapy, 55*(4), 369–376. PubMed ID: 11723980 doi:10.5014/ajot.55.4.369

Bower, K., Thilarajah, S., Pua, Y.H., Williams, G., Tan, D., Mentiplay, B., . . . Clark, R. (2019). Dynamic balance and instrumented gait variables are independent predictors of falls following stroke. *Journal of NeuroEngineering and Rehabilitation, 16*(1), 1–9. doi:10.1186/s12984-018-0478-4

Bril, B., Dupuy, L., Dietrich, G., & Corbetta, D. (2015). Learning to tune the antero-posterior propulsive forces during walking: a necessary skill for mastering upright locomotion in toddlers. *Experimental Brain Research, 233*(10), 2903–2912. PubMed ID: 26246420 doi:10.1007/s00221-015-4378-6

Caplan, P.J., & Kinsbourne, M. (1976). Baby dops the rattle: Asymmetry of duration of grasp by infants. *Child Development, 47*(2), 532–534. PubMed ID: 1269321 doi:10.2307/1128815

Carfagni, M., Furferi, R., Governi, L., Santarelli, C., Servi, M., Uccheddu, F., & Volpe, Y. (2019). Metrological and critical characterization of the Intel D415 stereo depth camera. *Sensors, 19*(3), E489. PubMed ID: 30691011 doi:10.3390/s19030489

Clark, R.A., Mentiplay, B.F., Hough, E., & Pua, Y.H. (2019). Three-dimensional cameras and skeleton pose tracking for physical function assessment: A review of uses, validity, current developments and Kinect alternatives. *Gait and Posture, 68,* 193–200. PubMed ID: 30500731 doi:10.1016/j.gaitpost.2018.11.029

Claxton, L.J., Keen, R., & McCarty, M.E. (2003). Evidence of motor planning in infant reaching behavior. *Psychological Science, 14*(4), 354–356. PubMed ID: 12807409 doi:10.1111/1467-9280.24421

Colquhoun, H.L., Levac, D., Brien, K.K.O., Straus, S., Tricco, A.C., Perrier, L., . . . Moher, D. (2014). Scoping reviews: time for clarity in definition, methods, and reporting. *Journal of Clinical Epidemiology, 67*(12), 1291–1294. PubMed ID: 25034198 doi:10.1016/j.jclinepi.2014.03.013

Colyer, S.L., Evans, M., Cosker, D.P., & Salo, A.I.T. (2018). A review of the evolution of vision-based motion analysis and the integration of advanced computer vision methods towards developing a markerless system. *Sports Medicine - Open, 4*(1), 24. PubMed ID: 29869300 doi:10.1186/s40798-018-0139-y

Credé, M., Tynan, M.C., & Harms, P.D. (2017). Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and social Psychology, 113*(3), 492–511. doi:10.1037/pspp0000102

Diedrich, F.J., Thelen, E., Smith, L.B., & Corbetta, D. (2000). Motor memory is a factor in infant perseverative errors. *Developmental Science, 3*(4), 479–494. doi:10.1111/1467-7687.00140

Duckworth, A., & Gross, J.J. (2014). Self-control and grit: Related but separable determinants of success. *Current Directions in Psychological Science, 23*(5), 319–325. PubMed ID: 26855479 doi:10.1177/0963721414541462

Duckworth, A.L., Peterson, C., Matthews, M.D., & Kelly, D.R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology, 92*(6), 1087–1101. PubMed ID: 17547490 doi:10.1037/0022-3514.92.6.1087

Fagot, B., Gauvain, M., & Kavanagh, K. (1996). Infant attachment and mother-child problem solving: A replication. *Journal of Social and Personal Relationships, 13*(2), 295–302. doi:10.1177/0265407596132008

Fetters, L., Sapir, I., Chen, Y.P., Kubo, M., & Tronick, E. (2010). Spontaneous kicking in full-term and preterm infants with and without white matter disorder. *Developmental Psychobiology, 52*(6), 524–536. PubMed ID: 20806325 doi:10.1002/dev.20455

Frankel, K.A., & Bates, J.E. (1990). Mother-toddler problem solving: Antecedents in attachment, home behavior, and temperment. *Child Development, 61*(3), 810–819. PubMed ID: 2364755 doi:10.2307/1130965

Frodi, A., Bridges, L., & Grolnick, W. (1985). Correlates of mastery-related behaviorâ€: A short-term longitudinal study of infants in their second year. *Child Development, 56*(5), 1291–1298. PubMed ID: 4053744 doi:10.2307/1130244

Gire, D.H., Kapoor, V., Arrighi-Allisan, A., Seminara, A., & Murthy, V.N. (2016). Mice develop efficient strategies for foraging and navigation using complex natural stimuli. *Current Biology, 26*(10), 1261–1273. PubMed ID: 27112299 doi:10.1016/j.cub.2016.03.040

Glenn, S., Dayus, B., Cunningham, C., & Horgan, M. (2001). Mastery motivation in children with Down syndrome. *Down Syndrome Research and Practice, 7*(2), 52–59. doi:10.3104/reports.114

Golinkoff, R.M. . (1986). 'I beg your pardon?': the preverbal negotiation of failed messages. *Journal of Child Language, 13*(3), 455–476. PubMed ID: 3793809 doi:10.1017/S0305000900006826

Grolnick, W., Frodi, A., & Bridges, L. (1984). Maternal control style and the mastery motivation of one-year-olds. *Infant Mental Health Journal, 5*(2), 72–82. doi: 10.1002/1097-0355(198422)5:2<72::AID-IMHJ2280050203>3.0.CO;2-O

Gusnard, D.A., Ollinger, J.M., Shulman, G.L., Cloninger, C.R., Price, J.L., Van Essen, D.C., & Raichle, M.E. (2003). Persistence and brain circuitry. *Proceedings of the National Academy of Sciences of the United States of America, 100*(6), 3479–3484. PubMed ID: 12626765 doi:10.1073/pnas.0538050100

Hamlin, J.K., Wynn, K., & Bloom, P. (2007). Social evaluation by preverbal infants. *Nature, 63*(3), 219. doi:10.1203/PDR.0b013e318168c6e5

Hauser-Cram, P. (1996). Mastery motivation in toddlers with developmental disabilities. *Child Development, 67*(1), 236–248. PubMed ID: 8605831 doi:10.2307/1131698

Insafutdinov, E., Pishchulin, L., Andres, B., Andriluka, M., & Schiele, B. (2016). *DeeperCut: A deeper, stronger, and faster multi-person pose estimation model*. Paper presented at the European Conference on Computer Vision, 34–50.

Jennings, K.D., Harmon, R.J., Morgan, G.A., Gaiter, J.L., & Yarrow, L.J. (1979). Exploratory play as an index of mastery motivation: Relationships to persistence, cognitive functioning, and environmental measures. *Developmental Psychology, 15*(4), 386–394. doi:10.1037/0012-1649.15.4.386

Kahrs, B.A., Jung, W.P., & Lockman, J.J. (2013). Motor origins of tool use. *Child Development, 84*(3), 810–816. PubMed ID: 23106197 doi:10.1111/cdev.12000

Kahrs, B.A., Jung, W.P., & Lockman, J.J. (2014). When does tool use become distinctively human? Hammering in young children. *Child Development, 85*(3), 1050–1061. PubMed ID: 24128178 doi:10.1111/cdev.12179

Kelley, S.A., Brownell, C.A., & Campbell, S.B. (2000). Mastery motivation and self-evaluative affect in toddlers: longitudinal relations with maternal behavior. *Child Development, 71*(4), 1061–1071.

Leonard, J.A., Lee, Y., & Schulz, L.E. (2017). Infants make more attempts to achieve a goal when they see adults persist. *Science, 357*(6357), 1290–1294. doi:10.1126/science.aan2317

Lewis, M., Sullivan, M.W., & Kim, H.M.S. (2015). Infant approach and withdrawal in response to a goal blockage: Its antecedent causes and its effect on toddler persistence. *Developmental Psychology, 51*(11), 1553–1563. PubMed ID: 26389608 doi:10.1037/dev0000043

Locher, R., & Ruckstuhl, A. (2012). *IDPmisc: Utilities of institute of data analyses and process design*. Retrieved from www.idp.zhaw.ch

Lockman, J.J., & Kahrs, B.A. (2017). New insights into the development of human tool use. *Current Directions in Psychological Science, 26*(4), 330–334. doi:10.1177/0963721417692035

Lucca, K., Horton, R., & Sommerville, J.A. (n.d.). Infants' rationally decide when and how to deploy effort.

Lucca, K., Horton, R., & Sommerville, J.A. (2019). Keep trying!: Parental language andinfants' persistence. *Cognition, 193,* 104025. PubMed ID: 31325720 doi:10.1016/j.cognition.2019.104025

Lucca, K., & Sommerville, J.A. (2018). The little engine that can: Infants' persistence matters. *Trends in Cognitive Sciences, 22*(11), 965–968. PubMed ID: 30122360 doi:10.1016/j.tics.2018.07.012

Lucca, K., & Wilbourn, M.P. (2019). The what and the how: Information-seeking pointing gestures facilitate learning labels and functions. *Journal of Experimental Child Psychology, 178,* 417–436. PubMed ID: 30318380 doi:10.1016/j.jecp.2018.08.003

Marchi, V., Hakala, A., Knight, A., D'Acunto, F., Scattoni, M.L., Guzzetta, A., & Vanhatalo, S. (2019). Automated pose estimation captures key aspects of General

Movements at eight to 17 weeks from conventional videos. *Acta Paediatrica, International Journal of Paediatrics, 108*(10), 1817–1824. doi:10.1111/apa.14781

Martin, A., Ryan, R.M., & Brooks-Gunn, J. (2013). Longitudinal associations among interest, persistence, supportive parenting, and achievement in early childhood. *Early Childhood Research Quarterly, 28*(4), 658–667. doi:10.1016/j.ecresq.2013.05.003

Maslin-Cole, C., Bretherton, I., & Morgan, G.A. (1993). Toddler mastery motivation and competence. In *Mastery motivation in early childhood: Development, measurement, and social processes* (pp. 205–229). London, UK: Routledge.

Matas, L., Arend, R.A., & Sroufe, L.A. (1978). Continuity of adaptation in the second year: The relationship between quality of attachment and later competence. *Child Development, 49*(3), 547–556. doi:10.2307/1128221

Mathis, A., Mamidanna, P., Cury, K.M., Abe, T., Murthy, V.N., Mathis, M.W., & Bethge, M. (2018). DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. *Nature Neuroscience, 21*(9), 1281–1289. PubMed ID: 30127430 doi:10.1038/s41593-018-0209-y

Mathis, A., & Warren, R. (2018). On the inference speed and video-compression robustness of DeepLabCut. *BioRxiv,* 457242. doi:10.1101/457242

Matsumoto, J., Uehara, T., Urakawa, S., & Takamura, Y. (2014). 3D video analysis of the novel object recognition test in rats. *Behavioural Brain Research, 272,* 16–24. PubMed ID: 24991752 doi:10.1016/j.bbr.2014.06.047

Matsumoto, J., Urakawa, S., Takamura, Y., Malcher-lopes, R., Hori, E., Tomaz, C., . . . Nishijo, H. (2013). A 3D-video-based computerized analysis of social and sexual interactions in rats. *PLoS ONE, 8*(10), e78460. PubMed ID: 24205238 doi:10.1371/journal.pone.0078460

McCarty, M., Clifton, R., & Collard, R. (1999). Problem solving in infancy: The emergence of an action plan. *Developmental Psychology, 35*(4), 1091–1101. doi:10.1037/0012-1649.35.4.1091

Mcgillivray, M., & White, H. (1993). Measuring development? The UNDP's human development index. *Journal of International Development, 5*(2), 183–192. doi:10.1002/jid.3380050210

Messer, D.J., McCarthy, M.E., McQuiston, S., MacTurk, R.H., Yarrow, L.J., & Vietze, P.M. (1986). Relation between mastery behavior in infancy and competence in early childhood. *Developmental Psychology, 22*(3), 366–372. doi:10.1037/0012-1649.22.3.366

Morgan, G., Harmon, R., Maslin-Cole, C., Busch-Rossnagel, N., Jennings, K., Hauser-Cram, P., & Brockman, L. (1992). *Assessing perceptions of mastery motivation: The dimensions of mastery questionnaire, its development, psychometrics and use*. Fort Collins, CO: Colorado State University.

Nakamura, T., Matsumoto, J., Nishimaru, H., Bretas, R.V., Takamura, Y., Hori, E., . . . Nishijo, H. (2016). A markerless 3D computerized motion capture system incorporating a skeleton model for monkeys. *PLoS ONE, 11*(11), e0166154. PubMed ID: 27812205 doi:10.1371/journal.pone.0166154

Nath, T., Mathis, A., Chen, A.C., Patel, A., Bethge, M., & Mathis, M.W. (2018). Using DeepLabCut for 3D markerless pose estimation across species and behaviors. *BioRxiv,* 476531. doi:10.1101/476531

Oppenheimer, J.E. (2011). *Understanding early vulnerabilities for anxiety: predictors of self-efficacy in toddlers* (Dissertation). University of Oregon.

Pham, M.T., Greig, J.D., Sargeant, J.M., & Mcewen, S.A. (2014). A scoping review of scoping reviews: Advancing the approach and enhancing the consistency. *Research Synthesis Methods, 5*(4), 371–85. doi:10.1002/jrsm.1123

Pipp-Siegel, S., Sedey, A.L., Vanleeuwen, A.M., & Yoshinaga-itano, C. (2000). Mastery motivation and expressive language in young children with hearing loss. *Journal of Deaf Studies and Deaf Education, 8*(2), 133–145. doi:10.1093/deafed/eng008

Redding, R.E., Harmon, R.J., & Morgan, G.A. (1990). Relationships between maternal depression and infants' mastery behaviors. *Infant Behavior and Development, 13*(3), 391–395. doi:10.1016/0163-6383(90)90042-7

Redding, R.E., Morgan, G.A., & Harmon, R.J. (1988). Mastery motivation in infants and toddlers: Is it greatest when tasks are moderately challenging? *Infant Behavior and Development, 11*(4), 419–430. doi:10.1016/0163-6383(88)90003-3

Robin, D.J., Berthier, N.E., & Clifton, R.K. (1996). Infants' predictive reaching for moving objects in the dark. *Developmental Psychology, 32*(5), 824–835. doi:10.1037/0012-1649.32.5.824

Schieche, M., & Spangler, G. (2005). Individual differences in biobehavioral organization during problem-solving in toddlers: The influence of maternal behavior, infant-mother attachment, and behavioral inhibition on the attachment-exploration balance. *Developmental Psychobiology, 46*(4), 293–306. PubMed ID: 15832325 doi:10.1002/dev.20065

Schmitz, A., Ye, M., Boggess, G., Shapiro, R., Yang, R., & Noehren, B. (2015). The measurement of in vivo joint angles during a squat using a single camera markerless motion capture system as compared to a marker based system. *Gait and Posture, 41*(2), 694–698. PubMed ID: 25708833 doi:10.1016/j.gaitpost.2015.01.028

Siena, F.L., Byrom, B., Watts, P., & Breedon, P. (2018). Utilising the intel realsense camera for measuring health outcomes in clinical research. *Journal of Medical Systems, 42*(3), 1–10. doi:10.1007/s10916-018-0905-x

Snapp-Childs, W., & Corbetta, D. (2009). Evidence of early strategies in learning to walk. *Infancy, 14*(1), 101–116. doi:10.1080/15250000802569835

Sparks, T., Hunter, S., Backman, T., Morgan, G., & Ross, R. (2012). Maternal parenting stress and mothers' reports of their infants' mastery motivation. *Infant Behavior & Development, 24*(2), 167–173. doi:10.1016/j.infbeh.2011.07.002

Strelau, J., & Zawadzki, B. (1995). The formal characteristics of behaviour—Temperament inventory (FCB—TI): Validity studies. *European Journal of Personality, 9*(3), 207–229. doi:10.1002/per.2410090304

Sullivan, M.W., & Carmody, D.P. (2018). Approach-related emotion, toddlers' persistence, and negative reactions to failure. *Social Development, 27*(3), 586–600. PubMed ID: 30147252 doi:10.1111/sode.12285

Tamis-LeMonda, C.S., Bornstein, M.H., & Baumwell, L. (2001). Maternal responsiveness and children's achievement of language milestones. *Child Development, 72*(3), 748–767. PubMed ID: 11405580 doi:10.1111/1467-8624.00313

Thelen, E, Corbetta, D., & Spencer, J.P. (1996). Development of reaching during the first year: role of movement speed. *Journal of Experimental Psychology. Human Perception and Performance, 22*(5), 1059–1076. PubMed ID: 8865616 doi:10.1037/0096-1523.22.5.1059

Thelen, E., Ulrich, B.D., & Niles, D. (1987). Bilateral coordination in human infants: Stepping on a split-belt treadmill. *Journal of Experimental Psychology. Human Perception and Performance, 13*(3), 405–410. PubMed ID: 2958589. doi:10.1037/0096-1523.13.3.405

Tricco, A.C., Lillie, E., Zarin, W., Brien, K.O., Colquhoun, H., Kastner, M., . . . Straus, S.E. (2016). A scoping review on the conduct and reporting of scoping reviews. *BMC Medical Research Methodology, 16*(1), 15. PubMed ID: 26857112 doi:10.1186/s12874-016-0116-4

Von Hofsten, C., & Rosander, K. (1997). Development of smooth pursuit tracking in young infants. *Vision Research, 37*(13), 1799–1810. PubMed ID: 9274766 doi:10.1016/S0042-6989(96)00332-X

Wachs, T.D. (1987). Specificity of environmental action as manifest in environmental correlates of infant's mastery motivation. *Developmental Psychology, 23*(6), 782–790. doi:10.1037/0012-1649.23.6.782

Wang, F., James, A., Snyder, P., Cox, M., Wang, F., Algina, J., & Snyder, P. (2017). Children's task engagement during challenging puzzle tasks. *Merrill-Palmer Quarterly, 63*(4), 425–457. doi:10.13110/merrpalmquar1982.63.4.0425

Wang, P.J., Hwang, A.W., Liao, H.F., Chen, P.C., & Hsieh, W.S. (2011). The stability of mastery motivation and its relationship with home environment in infants and toddlers. *Infant Behavior and Development, 34*(3), 434–442. PubMed ID: 21632116 doi:10.1016/j.infbeh.2011.04.005

Wiltschko, A.B., Johnson, M.J., Iurilli, G., Abraira, V.E., Adams, R.P., Wiltschko, A.B., . . . Datta, S.R. (2015). NeuroResource mapping sub-second structure in mouse behavior. *Neuron, 88*(6), 1121–1135. PubMed ID: 26687221 doi:10.1016/j.neuron.2015.11.031

Yarrow, L.J., Macturk, R.H., Vietze, P.M., Mccarthy, M.E., Klein, R.P., & Mcquiston, S. (1984). Developmental course of parental stimulation and its relationship to mastery motivation during infancy. *Developmental Psychology, 20*(3), 492–503. doi:10.1037/0012-1649.20.3.492

Yarrow, L.J., McQuiston, S., MacTurk, R.H., McCarthy, M.E., Klein, R.P., & Vietze, P.M. (1983). Assessment of mastery motivation during the first year of life: Contemporaneous and cross-age relationships. *Developmental Psychology, 19*(2), 159–171. doi:10.1037/0012-1649.19.2.159

Yarrow, L.J., Morgan, G.A., Jennings, K.D., Harmon, R.J., & Gaiter, J.L. (1982). Infants' persistence at tasks: Relationships to cognitive functioning and early experience. *Infant Behavior and Development, 5*(2–4), 131–141. doi:10.1016/S0163-6383(82)80023-4