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Perceiving Soft Tissue Break Points in the Presence of Friction

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PERCEIVING SOFT TISSUE BREAK POINTS IN THE PRESENCE OF FRICTION

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ABSTRACT

In minimally invasive surgery (MIS), surgeons face several perceptual challenges due to the remote interaction with the environment, such as distorted haptic feedback through the instruments due to friction produced from the rubber trocar sealing mechanisms at the incision site. As a result, surgeons sometimes unintentionally damage healthy tissues during MIS due to excessive force. Research has demonstrated that useful information is available in the haptic array regarding soft tissues, which allows novices to successfully perceive the penetration distance remaining until a material will fail based on displacement and reactionary forces of simulated tissues using a haptic invariant, Distance-to-Break (DTB). Attunement and calibration training was used in the current study to investigate whether observers are able to identify material break points in nonlinear compliant materials through haptic force application, while ignoring haptic stimulation not lawfully related to the properties specifying DTB, including friction. A pretest, feedback, posttest, and transfer-of-training phase design allowed participants to probe four virtually simulated materials at varying levels of friction: no friction, low friction, and high friction in the first experiment, and pull the simulated tissues in the second experiment to investigate if perception of DTB generalizes to other tasks used in MIS. Experiment 1 revealed that sensitivity to DTB can be improved through training, even in the presence of friction, and that friction may assist observers to perceive fragile tissues that otherwise would be below perceptual threshold. Experiment 2 revealed that attunement and calibration to DTB also transfers to pulling motions.

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CHAPTER ONE

PERCEIVING SOFT TISSUE BREAK POINTS IN THE PRESENCE OF FRICTION

Minimally invasive surgical techniques offer patients the promise of smaller incisions, reduced damage to the body, less pain, and shorter recovery times by inserting long instruments and an endoscopic camera into small incisions via trocars (Breedveld & Wentink, 2001; Bathea et al., 2004). Although traditional open surgeries allow the surgeon to directly manipulate internal body organs and tissues through a large opening, new technologies have allowed for a rise in minimally invasive surgery (MIS) procedures, which require the surgeon to manipulate tissues indirectly through laparoscopic tools and view the operation indirectly on a two-dimensional monitor. Due to the challenging visual conditions and the unintuitive nature of tool manipulation with MIS, a large amount of training is required to develop these skills, which is often performed with the use of simulators. In fact, there are more surgical training simulators available for laparoscopic training than any other type of medical training task (Coles, Meglan, & John, 2011).

Research suggests that surgeons sometimes unintentionally damage healthy tissues during MIS procedures. For example, in 60 simulated cholecystectomies performed by 60 surgical trainees, use of excessive force was the third most common type of error committed, with 187 occurrences recorded during the 60 procedures (Tang, Hanna, & Cuschieri, 2005). All instances of tissue damage were determined to be the result of excessive force. Injuries of bile ducts during a cholecystectomy occur three times more often in laparoscopic surgery than in open surgery (Archer, Brown, Smith, Branum, & Hunter, 2001; Traverso, 1999). Out of approximately 500,000 patients receiving a laparoscopic cholecystectomy each year, about 1,500 to 2,000 will experience damage to the bile ducts (Hugh, 2002). A great majority of these damages during cholecystectomy are caused by errors in perception, rather than errors in skill, knowledge, or judgment, with surgeons injuring unseen bile ducts during dissection or deliberately cutting a bile duct when he or she believed it to be something else (Way et al., 2003).

MIS training and perceptual problems

Despite documented benefits of using MIS methodologies rather than open surgery, surgeons face several perceptual challenges with MIS similar to other environments where an operator is controlling or viewing an object remotely. For example, humans struggle to perceive depth and size of objects in virtual or remote environments, underestimating egocentric distances (0m – 30m) by as much as 50% (Altenhoff et al., 2012; Napieralski et al., 2011; Richardson & Waller, 2005; Thompson et al., 2004; Witmer & Kline, 1998). Tittle, Roesler, and Woods (2002) have termed these difficulties “the remote perception problem.” Unlike open surgery, where a surgeon can look directly into the operative scene and see his/her hands and tools manipulating the scene, during MIS the surgeon views a monitor, which produces a mislocation of the endoscope and prevents the surgeon from being able to simultaneously observe his/her hands and the scene. This difference between the endoscope’s viewpoint and the surgeon’s viewpoint as if he/she were looking directly into the abdomen produces a variety of perceptual challenges that the surgeon must overcome. Because the instruments rotate around the incision point through a trocar, surgeons must translate a mirrored image produced during sweeping, side-to-side motions, which is also magnified on the monitor, further contributing to the scaling challenges as experienced in other remote environments. Depending on how far the instrument is inserted, the surgeon's movements may produce a magnified or reduced effect on the instrument tip. Additionally, the endoscope is usually controlled by someone other than the surgeon, which can cause the endoscope's viewpoint to be different from what the surgeon's would be if he/she looked down into the abdomen (Breedveld & Wentink, 2001). In addition to viewing a rotated view of the surgery, surgeons are passively viewing the scene as the assistant controls the camera, which breaks the perception-action link present in regular environments (Tittle et al., 2002; Gomer, Dash, Moore, & Pagano, 2009).

Haptics: Tactile and Kinesthetic Info

Not only does the remote perception problem in MIS procedures make it difficult for surgeons to accurately perceive visual information on the monitor, but the arrangement also creates distorted haptic feedback through the surgeon's instruments (Den Boer et al., 1999; Van den Dobbelsteen, Schooleman, & Dankelman, 2007). Just as the surgeon cannot directly see the tissues he or she is operating on, organs and tissues are touched indirectly and softness is assessed with surgical tools rather than his or her hands. The haptic feedback a surgeon receives in open surgery when directly touching soft tissue consists of both tactile information (cutaneous stimulation) and kinesthetic information. When the tissue or organ is touched or squeezed, the sense of touch, or tactile information, is perceived via sensory receptors in the finger tips. Kinesthetic information is the sense of one's body position and movement, wielded objects, and probed surfaces communicated by receptors in joints, tendons, muscles, and skin (Loomis & Lederman, 1986, Pagano & Cabe, 2003; Pagano, Carello & Turvey, 1996; Pagano & Donahue, 1999; Perreault & Cao, 2006; Srinivasan & LaMotte, 1995; Turvey, 1996). Together, tactile and kinesthetic information make up a person's haptic sense. Though both haptic and kinesthetic information both play a role in the surgical task, kinesthesis is primarily responsible for providing information about the interactions between the distal ends of the tools and the properties of the tissue.

As surgeons apply force onto body organs and tissues, they can immediately obtain useful haptic information based on the compliance of the tissue. However, because tactile information has been shown to be useful when discriminating between deformable materials (Srinivasan & LaMotte, 1995), surgeons must alter how they judge compliancy of materials with only indirect contact through the tools. Relying primarily on kinesthesis, the amount of tissue displacement or resistance in response to the amount of force applied reveals useful property information about the compliancy, or softness, of a tissue to the surgeon (Bergman Tiest & Kappers, 2009; Vincentini & Botturi, 2009; Srinivasan & LaMotte, 1995). This compliancy and stiffness information gained from force feedback gives information about fragility and may specify motor adjustments necessary to avoid damaging materials. Although vision can offer some clues about compliancy as tissue is displaced in response to forces, we know that the visual information available in MIS is also distorted by unnatural camera angles, ambiguous scaling, and lack of stereoscopic information. Even if the operation were viewed directly, vision does not provide any information about force being applied or reactionary force from the tissue, which is necessary to determine the compliancy of a material. Vision alone does not provide enough information to accurately judge softness or fragility of a material (Srinivasan & LaMotte, 1995; Klazky, Lederman, & Matula, 1993; Smyth & Waller, 1998).

It is important that surgeons are trained to pick on useful haptic information in this new environment. Evidence suggests that haptic feedback does improve performance in both MIS tasks and basic laparoscopic training tasks, particularly when pushing or pulling (Chmarra, Dankelman, van den Dobbelsteen, & Jansen, 2008). When performing a dissection task robotically without force feedback, gynecologic residents participants applied 50% more force than with force feedback and committed three times the number of injury-causing errors (Wagner, Stylopoulos, & Howe, 2002). Particularly, research demonstrates that receiving haptic feedback in a virtual training environment may be especially critical during early training phases for psychomotor skill acquisition (Ström et al., 2006). Due to the indirect contact with the tissue, future surgeons have to learn about force feedback before they can safely conduct actual surgery. For example, during surgery the operator may perceive forces 0.2-4.5 times the force generated. Realistic simulators with haptic feedback are thought to lead to better overall performance, faster learning, and high transfer of skill to operating on actual tissue (van der Meijden, & Schijven, 2009). Some warn that learning tasks in VR without realistic haptic feedback may result in negative learning effects when these tasks are completed on actual tissue, where appropriate application of force plays an important role in surgical performance

(Chmarra et al., 2008; Srinivasan & LaMotte, 1995). Despite extensive training, typically developing expert eye-hand coordination skills, no haptic skills training in detecting tissue break point or force perception is required.

Direct Perception and the Haptic Array

Similar to the well-studied lawful relationships available in the optic array of looming and time-to-contact (Lee, 1976; Hecht & Savelsbergh, 2004), research has also demonstrated that information is available in the haptic array of soft tissues that specifies to a surgeon when a tissue will break (Long et al., 2014). As surgeons apply a given amount of force to a soft tissue, the resulting displacement grows less and less as they probe deeper, indicating that the tissue is becomingly increasingly stiff and that it may soon break. This changing compliancy in human tissue is often the result of a lawful, biomechanical relationship (Brouwer et al., 2001; Carter, Frank, Davies, McLean, & Cuscheri, 2001; Fung, 1993; Rosen, Brown, De, Sinanan, & Hannaford, 2008; Yamada, 1970) – one which surgeons may be able to attune to in order to perceive how much farther they can probe before breaking the tissue. If trained to accurately interpret these lawful relationships, surgeons should better understand the structural capacity of human tissues, allowing them to apply more appropriate forces and reduce trauma or breakage of healthy tissues.

Based on research and theories of J. Gibson (1950, 1966, 1979), many have studied ways in which the human perceptual system is able to attune to information available in an ambient stimulus array (Long, et al., 2014; Cabe & Pittenger, 1992; Cabe, 2011), particularly in the optic array (Gibson 1966, 1979; Lee, 1976; Bingham & Pagano, 1998). According to Gibson (1966, 1979), information in the optic/haptic array that follows the laws of physics reveals invariants to an observer, which can be used to guide actions. For example, looming of an object in the environment on an observer's retina can be perceived through information in the light. As the distance between the object and the observer decreases, the rate of expansion specifies to the observer the time until one will make contact with the object, known as time-to-contact (TTC). Lee (1976) demonstrated that TTC provides actionable information to an observer, based on the relationship between the distance between the object and the observer (area on the retina) and velocity (rate of change on the retina), which he labeled tau (see Figure 1). For example, as an observer approaches a stop sign, the sign subtends a larger and larger amount of space in the visual field. As the area of the sign increases on the retina, the observer perceives the distance between themselves and the sign to decrease. This relative rate of expansion of the sign is expressed as:

$$\textit{Relative Rate of Expansion} = \frac{\Delta Area/\Delta Time}{Area}$$

The inverse specifies TTC, which denotes time remaining until the distance between the observer and the sign reaches zero, and is expressed as:

$$TTC = \frac{Area}{\Delta Area/\Delta Time}$$

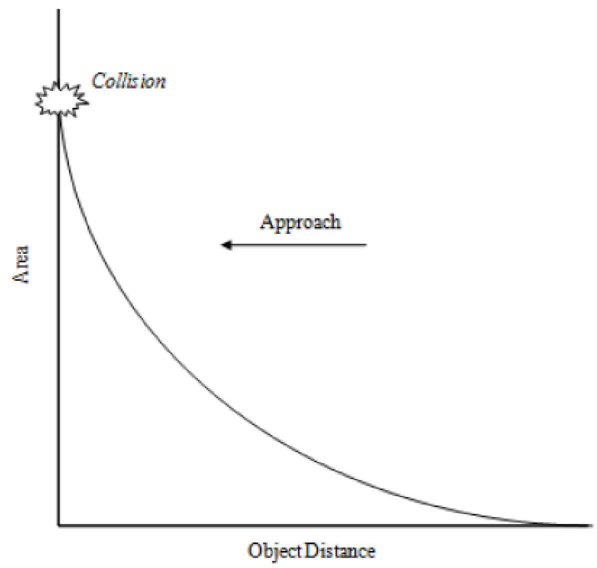

Figure 1. Relationship between an object's distance and the size of its projection on the retina.

If the observer is sensitive to TTC, they can perceive the time remaining before the distance reaches zero without computing lower-order variables such as velocity, object size, or object distance. Since, researchers have also examined looming and similar relationships in other modalities, such as acoustic TTC (Shaw, McGowen & Turvey, 1991), time-to-topple based on haptic information (Cabe & Pittenger, 1992), impending contact based on acoustic information (Schiff & Oldak, 1990), and haptic looming (Cabe, 2011). Thus, it is likely that relationships similar to TTC exist in the haptic array when approaching the break point while deforming a soft tissue.

Distance-To-Break (DTB)

Tissue compliancy is perceived through the amount of tissue displacement or resistance in response to the amount of force applied, which gives the surgeon information about fragility (Bergman Tiest & Kappers, 2009; Vincentini & Botturi, 2009; Srinivasan & LaMotte, 1995), and may offer information specifying the distance remaining until the material breaks. Many soft biological tissues follow an exponential stress-strain pattern (Brouwer et al., 2001; Carter, Frank, Davies, McLean, & Cuscheri, 2001; Fung, 1993; Rosen, Brown, De, Sinanan, & Hannaford, 2008; Yamada, 1970) where the reactionary forces increase in an exponential fashion as the displacement into the tissue increases towards the point of failure until the tissue finally breaks as the structural limits are reached. Long et al. (2014) demonstrated that participants can successfully perceive the penetration distance remaining until a material will fail based on displacement and reactionary forces of simulated tissues using a haptic invariant comparable to TTC, Distance-to-Break (DTB).

$$DTB = \frac{Force}{\Delta Force / \Delta Displacement}$$

Similar to TTC, DTB is a higher-order parameter that does not require the computation of lower-order variables such as force or tissue stiffness. Rather, it is the ratio between the amount of force applied and the change in reactionary force as displacement increases. As force is applied, deformation of the material and reactionary forces specify to the operator the amount of displacement which the tissue can tolerate before breaking (See Figure 2). Using nine different tissue profiles with varying break point distances and varying forces required to break each material, Long et al. (2014) demonstrated that novice participants are sensitive to DTB and can improve the perceptual skill of judging break points with a brief training phase through attunement and calibration.

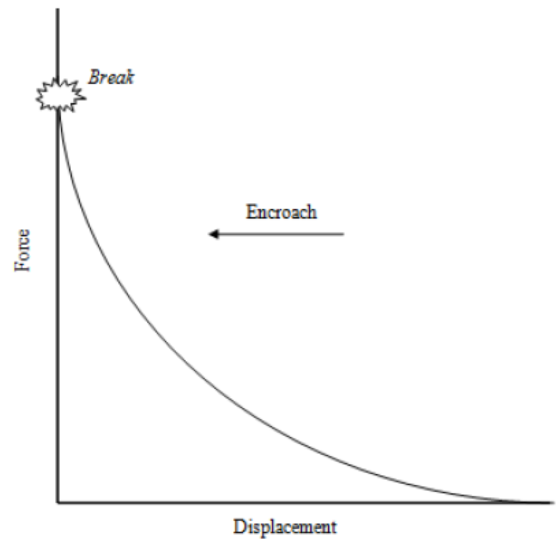

Figure 2. Relationship between soft material displacement and mechanical force required for that displacement.

Training Perception of DTB

Virtual environments (VE's) are a common means for providing training for situations that are dangerous, expensive, rare, or remote, such as laparoscopic surgery training (Bliss, Tidwell, & Guest, 1997; Darby, 2000; Peters et al., 2008). A main advantage of virtual environments is that they provide a controlled scenario so users can repeatedly and safely interact with situations. Due to the nature of MIS tasks, training on actual patients would be too dangerous and though cadavers and animal tissues are sometimes an option, it is often expensive, allowing the training surgeon minimal errors before being rendered useless (Coles, Meglan, & John, 2011). However, medical simulators are becoming an increasingly accepted tool for the extensive training necessary to prepare surgeons. Medical simulators provide a safe, yet realistic environment in which the surgeon can practice a task repeatedly and frequently to help maximize learning with the freedom to make mistakes.

With practice, it may be possible to increase sensitivity to DTB by improving observers' ability to discriminate the useful and meaningful properties available within the haptic array (Gibson, 1953; 1963; 1969; Gibson & Gibson, 1955). Virtual simulators provide an opportunity for novices to experience frequent, repeated haptic interaction with tissues, providing an ideal scenario for perceptual learning (i.e. training). Sensory systems are continually exposed to limitlessly rich information available for haptic perception that may or may not convey useful perceptual information about object properties. Through experience and feedback, perceivers attend to the useful information, and haptic perception becomes 'tuned' to the mechanically useful properties lawfully related to perceptual variables, known as *specifying* variables (Wagman, Shockley, Riley, & Turvey, 2001; Withagen & Michaels, 2005). Before feedback, perceivers perceptually estimate an object property based on a combination of variables, both specifying and non-specifying variables, which are ambiguously related to the property. Referred to as "education of attention" or "attunement", observers learn to converge on the variables that are most correlated with the object property and which accurately predict it, attuning to the salient perceptual invariants that specify useful information (Gibson & Gibson, 1955; Gibson, 1963; Withagen & Michaels, 2005).

The theory is that learning is more efficient when it involves perceptual attunement to meaningful information as opposed to the acquisition of complex mental structures. Over time, the perceptual system's output is also correctly scaled for accurate perceptual judgments, resulting in calibration of haptic perceptual systems (Withagen & Michaels, 2005). Previous research in our lab has found such performance improvements, with accuracy of participant force applications during probing, grasping, and/or sweeping movements improving after experiencing a training phase, which incorporates visual feedback (Singapogu et al., 2011, 2013, in press; Long et al., 2012, 2014). Attunement and calibration training will be used in the current study to improve the ability of observers to perceive material failure points.

Trocar Friction

Although Long et al. (2014) were able to demonstrate that perceiving DTB is a trainable perceptual skill, several other factors must be taken into consideration to make sure the training transfers to actual MIS procedures before a DTB training program can be fully developed. For example, basic research needs to demonstrate that training on the Core Haptic Skills Simulator transfers to perceiving DTB in real human tissues. Also, more research is needed to investigate how participants learn to perceive DTB with the other motions performed during MIS surgery such as pulling, sweeping, and grasping (Singapogu et al., 2012b) and with haptic sensations more representative of the forces generated by multiple interactions within the MIS environment. Not only do surgeons receive force feedback from applying pressure to internal organs and tissues, but the trocars, abdominal wall, and mass of the instrument alter the haptic feedback to the surgeon as well (Picod, Jambon, Vinatier, & Dubois, 2004). Trocars are a sealing mechanism, made of short tubes at the site of the incision that act as a portal for tools to access the body organs and/or tissues and often maintain pressure within the body cavity when fluid or gas is pumped in to better expose the surgical site.

Because injury inflicted on tissues during MIS tends to be more frequent than in open surgery, it is imperative that surgeons learn to reduce the inappropriate over-application of forces which damage healthy tissues. It's possible that many surgeons learn to ignore many of the complex haptic forces and compensate by visually observing the deformation of tissue as force is applied. However, vision will not always provide enough information to a surgeon to perceive when a tissue is about to fail (Srinivasan & LaMotte, 1995; Klazky, Lederman, & Matula, 1993; Smyth & Waller, 1998), particularly if an unhealthy or abnormal tissue visually appears to be normal. As discussed by Way et al. (2003), a great majority of these damages during cholecystectomy are caused by errors in perception, rather than errors in skill, knowledge, or judgment. Although the surgeon is operating indirectly on a patient and challenged with issues of the remote perception problem, some believe the friction generated by the rubber seal in the trocar to be the most significant contributor to perceptual challenges which surgeons are sometimes not able to overcome (Perreault & Cao, 2006).

In order to accurately attune to information of the biomechanical properties inherent in DTB, surgeons must be able to ignore haptic stimulation that is not relevant to the properties that are trying to perceive (i.e. non-specifying variables), including friction. But because the friction of the trocar can be relatively large compared to from the forces associated with the interactions between the tool and tissue, surgeons may not perceive that a tissue is near failure if it is very compliant or fragile. One may have to probe harder in order to perceive the compliancy of a soft tissue, especially if the haptic feedback from friction is very high. Friction varies based on the type of trocar, the movement velocity and direction of the surgeon's pushing or pulling gestures, and moistness (van den Dobbelsteen, Schooleman, & Dankelman, 2007).

Perreault and Cao (2006) demonstrated that trocar friction may cause an increased haptic perception threshold, with novices applying more force and taking more time to detect contact with tissue when friction is present. Early in training, surgeons must learn how to operate despite this challenge. It's possible that some surgeons are already attuning to DTB or other haptic skills to differentiate between useful haptic information and non-specifying variables, while others choose to rely on visual information about deformation. It is hypothesized that people can learn to ignore trocar friction, similar to the way the human perceptual system has been shown to accurately perceive the length of a rod by attuning to the invariant of inertia, ignoring the effects of wielding in different media such as air and water (Pagano & Cabe, 2003; Pagano & Donahue, 1999). Also, Lamata et al. (2008) demonstrated that surgeons were able to discriminate between four different tissues with only force information available, despite large amounts of force feedback from trocar friction. The goal of this research is to train participants how to attune to DTB and ignore other non-specifying variables so they can appropriately make use of perceptual information from visual and haptic modalities.

Purpose and Goals

Experienced surgeons have demonstrated the skills to accurately produce and perceive haptic forces, although it is unlikely that they were specifically trained how to attune to those forces. Training devices are currently being developed that are specifically devoted to training haptic skills. Trainees have shown significant improvement even after only a brief training period, demonstrating that it is a learnable skill (Singapogu et al., 2012a; Singapogu et al., 2012b). Although few experiments have investigated the effect of haptic feedback in a virtual environment (VE) simulator, the majority of research supports the idea that haptic feedback should be incorporated into VE training based on findings on the importance of haptics in minimally invasive surgery (Singapogu et al., 2012a).

Two experiments are designed to investigate whether observers are able to perceive DTB in nonlinear compliant materials through haptic force application, even with a simulated friction term added to the force feedback, and then use this information to identify the distance remaining until mechanical failure. The first experiment will test four hypotheses:

1. Participants are sensitive to DTB
2. Participants can detect DTB with varying friction levels present
3. Ability to locate DTB with varying levels of friction is a skill that can be improved through training.
4. Sensitivity to DTB will transfer to a task where participants must stop before the break point is reached

The second experiment will test one additional hypothesis:

5. Sensitivity to DTB generalizes to a pulling task.

Procedure and materials used are very similar to those used by Long et al. (2014). The first experiment examined to see if participants' perception of DTB is altered by the presence of varying levels of simulated trocar friction. Similar to Pagano and Cabe (2003; Pagano & Donahue, 1999), which demonstrated that participants were able to attune to a mechanical invariant, inertia, even when other forces (e.g. water resistance) were included, we expect novices to attune to DTB of different nonlinear materials while ignoring other forces. This experiment also examined participants' ability to improve perception of DTB with training. It is possible to increase an observer's reliance on perceptual invariants with feedback and practice attuning to the relevant information in the stimulus array (E. Gibson, 1969; J. Gibson, 1966; Withagen & Michaels, 2005). With experience, the useful information will become more distinct within the haptic array as the perceptual system identifies them as being lawfully related to material properties of the tissue predicting failure. Once an observer becomes more sensitive, or attunes, to the relevant mechanical properties, continued feedback will allow the haptic perceptual system to calibrate, becoming more sensitive to the useful mechanical properties as useful information is scaled for accurate perceptual judgments. Attunement and calibration have been shown to improve perceptual judgments of kinesthetic properties through training and feedback (Long, et al., 2012, 2014; Singapogu, et al., 2013, 2014; Wagman et al., 2001; Withagen & Michaels, 2005). With training, attunement and calibration should allow participants to become sensitive to the mechanical information specifying the location of material failure points and improve judgments of DTB.

CHAPTER TWO

EXPERIMENT ONE

To test for effects of attunement and calibration, probing of simulated materials was evaluated with a pretest, feedback, posttest, and transfer-of-training phase design, with performance data in the pretest addressing Hypothesis 1, that participants are able to detect DTB with friction present, and performance data in the posttest and transfer-of-training phases addressing Hypothesis 2, that DTB is a trainable skill that participants can calibrate with training. Friction was simulated in some trials during each of the four phases. To allow free exploration of probing materials without revealing feedback of break point judgments during pretest and posttest phases, materials were designed to provide useful information as the participant rode the nonlinear curve of the biomechanical properties of the tissue, but not actually break at the breaking point. Rather, at the point of mechanical failure, the tissues' force profile "flattened out" by maintaining forces as they were presented at the point of failure. During the feedback phase, feedback was provided visually. To investigate effects of DTB attunement in a more realistic MIS scenario, further validating training capability of the Core Haptic Skills Trainer, the transfer-of-training phase presented virtual materials to participants that actually "broke" at the appropriate breaking point. These two types of presentations are referred to as Task 1 and Task 2.

Task 1 is an exploratory break detection phase which allows participants to freely explore various simulated materials by pushing, or probing, into the material with a laparoscopic tool. Similar to other training simulators, the Core Haptic Skills Simulator allows participants to explore the theoretical materials with great variety of force applications, breaking materials numerous times, without the negative consequences as in actual surgery. Participants were encouraged to examine each tissue to indicate the location at which they believe it feels as if it should break, applying forces both greater than and less than what the virtual mechanical could withstand. Task 2 presented virtual nonlinear materials that truly "broke", examining if participants could successfully detect DTB without breaking the simulated material. During the transfer-of-training phase, Task 2 instructions were used, instructing participants to probe as close as possible to the breaking point without actually breaking the material. In order to successfully complete this task, participants had to perceive the location of the material's breaking point before actually tearing the material.

Methods

Participants

50 university undergraduate students between the ages of 17 and 22 (M = 18.2, SD = 0.7) participated in Experiment 1 after providing informed consent, none of whom had any experience practicing MIS. 35 were female and 15 were male. Participants received course credit in exchange for their participation.

Materials & Apparatus

1. Simulator

Nonlinear soft tissues were rendered using the Core Haptic Skills Trainer, a simulator developed at Clemson University with the purpose of training force-based skills in laparoscopic surgery. The simulator emulates three different force-based skills identified as particularly salient in minimally invasive surgery; grasping, probing, and sweeping (see Singapogu et al., 2011, 2012a, 2012b, 2013). Probing was used in the present study.

The force-based skills were integrated into a comprehensive simulator containing a single input device permitting the user to make discrete probing, grasping, and sweeping motions (see Figure 3). The input device was a laparoscopic surgical forceps tool with a scissor grip handle with pinchers removed (a Covidien Autosuture™ Endo® device, Dublin, Ireland). A robotic motion system delivered force feedback to the input device through two direct-drive DC motors (Tohoku Rioch™, Miyagi 987-0511, Japan) located at the center and the end of the forceps shaft. Through a series of computer algorithms, the system renders force feedback by generating a torque in response to user motion.

Haptic feedback rendered by the simulator emulates the tool coming into contact with and encroaching into an amenable mass, such as soft tissue. For probing, the user applies force through the input device by gripping the handles of the input device and pushing the tool forward. Advancing the tool produced feedback imitating coming into contact with and then pushing onto soft tissue, effectively simulating the tensile forces experienced as one stretches soft tissue.

Task 2 is designed to present haptic feedback which would render the simulated material truly ‘breaking,’ or failing, when excessive force is applied. As the user applies more force through the input tool, resistive force feedback increases at an exponential rate. Once the applied force becomes great enough, resistive feedback will immediately cease, emulating a soft tissue perforation.

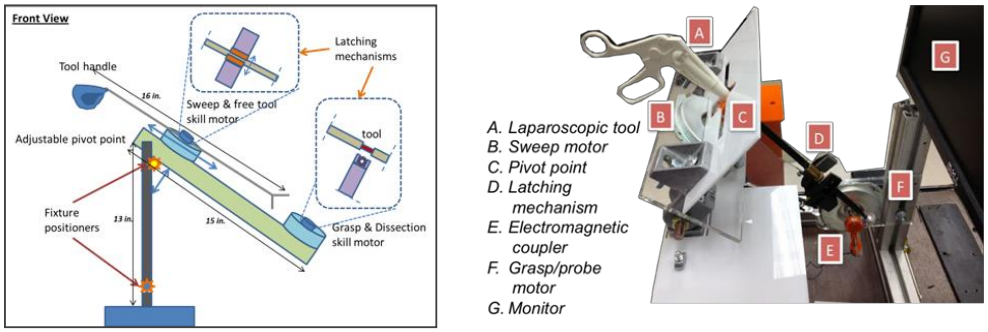

Figure 3. Schematic and photographic representation of the Core Haptic Skills Training Simulator (Singapogu, et al., 2013).

2. Visual feedback

Visual feedback was incorporated into the feedback training phase, allowing participants to view errors and then adjust, or calibrate, their force application after each trial. The feedback was presented by a custom visual graphic displayed on a monitor, which indicates tool position and placement along the simulated material (see Figure 4). The graphic included a movable red vertical, dynamic bar indicating normalized probed distance and a fixed blue vertical bar indicating the actual break point position. The red marker was proportional to the placement of the tool, and moved in response to increasing and decreasing applied force through the surgical input tool. At the starting position, the marker was located at the far left, moving from left to right as force is applied. Because the breaking point for each simulated material varied, relative to the material profile itself (described in detail below), the indication for break point in the graphic was static. Thus, the location of the break point in the graphic did not change;

only the application force required to move the indicating marker varied. Participants were asked to make their estimate of where they would place the tool to arrive as close to the designated break point as possible without going past. Once a participant verbally indicated they had made their estimate, they held the position of the tool while the experimenter made the graphic display available so the participant was able to view where their estimate was located relative to the break point. Participants were then asked to adjust the tool as necessary to align it with the break point.

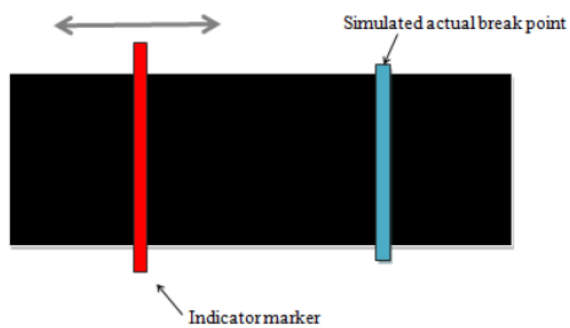

Figure 4. Visual graphic used in calibration feedback phase (Long et al., 2014).

3. Simulated Material Profiles

Four different nonlinear materials were simulated, based on profiles similar to soft tissues exhibiting exponential stress-strain relationships in response to compressive and tensile force loadings (Brouwer et al., 2001; Fung, 1993; Rosen, et al., 2008). The four compliance profiles and breaking points were designed to be the product of two different material strengths (F) at four different displacement locations (d) (see Figure 5). Thus, each material contained a different point of failure, or location at which it would 'break.' Observers could not rely solely upon one varying dimension or the other when correctly determining DTB, but must rely on the invariant relationship between the two of them.

As one dimension is modified and the point of failure changes, the relationship will still be maintained, which should be sufficient for specifying DTB.

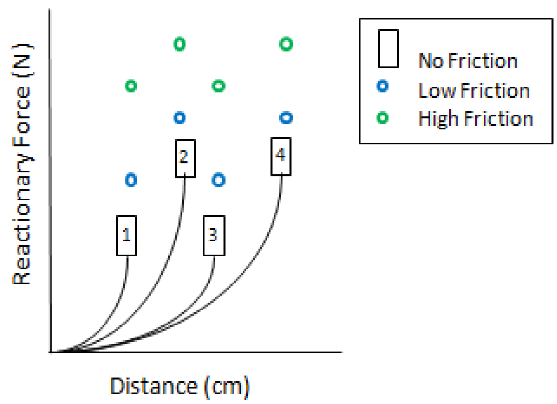

Figure 5. The four simulated material profiles and their designated breaking point location.

Each of the four materials were presented with varying amounts of simulated trocar friction: no friction (0N), low friction (1.5N), and high friction (3N). This range of friction levels encompasses the actual trocar friction observed, which can range from 0.25 N to 3 N (van den Dobbelsteen, Schooleman, & Dankelman, 2007). Thus, during pretest, posttest, and transfer-of-training phases, participants examined each material with no added friction, with low levels of trocar friction, and high levels of trocar friction. During the calibration phase, only three materials were used (see Figure 7). Tables 1a, 1b, and 1c display all of the metrics defining the nonlinear characteristics for each material profile, including break point distance and reactionary force.

Procedure

This experiment used a pretest, feedback, posttest, transfer-of-training model to examine attuning and calibration effects to DTB. The pretest provided a pre-training baseline to compare with posttest performance after feedback training. An additional transfer task evaluated the degree to which DTB perceptual skill carried over to a novel, more realistic MIS task. On the initial day of testing, participants who provided informed consent completed the pretest after an introductory training phase, which allowed participants to survey a single nonlinear material, helping them become comfortable with the laparoscopic tool and the task. Within the next seven days, participants returned for the feedback training phase, posttest, and transfer-of-training phases.

1. Pretest Phase

For the first phase, participants completed what has been defined as Task 1. They applied forces up to and beyond a hypothetical break point for four simulated materials presented at 3 varying levels of simulated trocar friction (no friction, low friction, and high friction), with the goal of identifying the location at which the material should fail (see Figure 7). Each material was presented three times with no friction, three times with low added friction, and three times with high added friction (4 materials x 3 friction levels x 3 presentations), for a total of 36 trials. No visual feedback was provided and once the break point was reached, the material did not actually break so as to minimize haptic feedback indicating successful judgment of DTB. They could freely explore the material at whatever speed they feel most comfortable. Participants made their estimates by suspending their force application and verbally designating their estimate to the experimenter. The experimenter logged the trial in MatLab, which captured the applied force and distance at that moment. At the end of each trial, the participant returned the surgical tool to the starting position before beginning the next trial.

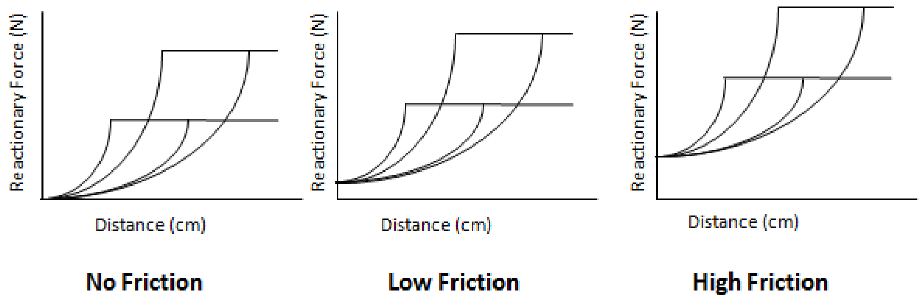

Figure 6. The four simulated material profiles and their hypothetical breaking point location displayed during the pretest and posttest phases.

2. Feedback training phase

When participants returned for the second day of the experiment they completed the training phase, which followed the same procedures as the pretest, but incorporated the visual feedback graphic to allow participants to calibrate their haptic estimate, and utilized for only three of the four experimental tissue profiles at two levels of friction (3 materials x 2 friction levels x 4 presentations) for a total of 24 trials. The feedback training phase was completed two to eight days after the pretest phase (M = 4.1, SD = 1.8). Participants were informed that the goal of the training is to learn to apply sufficient force onto each simulated profile without 'breaking' the material. Similar to the pretest, participants were allowed to freely explore the material at any speed or direction. They were also instructed that identifying the failure point should occur *before* reaching the breaking point, and that later phases will score excessive force applications as an error.

Similar to the pretest, participants indicated the location of the hypothetical breaking point, although rather than immediately returning to the starting position for the next trial, they were then shown a visual graphic of their performance, allowing them to calibrate and make adjustments to their haptic estimate (see Figure 4). The task was to locate the designated breaking point along the three materials depicted in Figure 7, again applying the amount of force they believed was required to puncture, or break, the material. After receiving feedback, the participant was allowed to adjust the tool to feel the appropriate 'break' point. In order to examine practice effects, half of the participants were randomly assigned to participate in a control condition, in which they completed the same task as the pretest during what would be the feedback phase for those in the experimental condition, resulting in a pretest, pretest, posttest, transfer-of-training model.

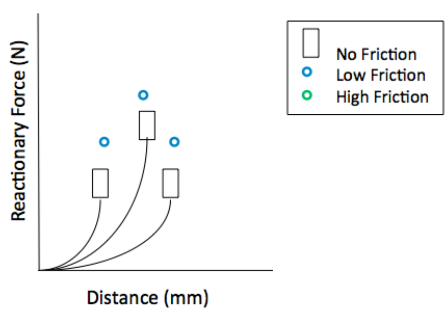

Figure 7. The three simulated material profiles and their designated breaking point location displayed during the feedback training.

3. Posttest phase

Participants took a five-minute break between concluding the feedback training phase and beginning the posttest phase, which used the same protocol and the same four materials as the pretest phase. As in the pretest, each material was presented three times with no friction, three times with low added friction, and three times with high added friction (4 materials x 3 friction levels x 3 presentations), all without any visual feedback, for a total of 36 trials.

4. Transfer-of-Training (ToT) Task

Participants took another five-minute break between concluding the posttest phase and beginning the transfer-of-training phase. The transfer task was similar to the first three phases, presenting the same four materials as in the pretest and posttest, except that the designated break point location within the simulated profiles was rendered to truly emulate breakage. As force was applied, the reactionary force of the material increased until a certain point at which the material failed (see Figure 8), haptically emulating puncture. The same four tissue profiles used in the pretest and posttest phases were used for this task, with the breaking points occurring at the same displacement location, although the material function approaches an asymptotic direction at the break point. Each participant was instructed to apply as much force as they could to the materials *without* breaking the material. During the instructions, they were given an analogy to better understand the task: like being near the edge of a cliff, the goal was to inch as close to the edge as possible without going over. Any trials in which a material was broken with excessive force were marked as an error, ending the trial, which were then represented at the end of the 36 original material presentations. Participants repeated trials of broken materials until they successfully complete the 36 trials (4 materials x 3 friction levels x 3 presentations). Performance was measured based on the proximity of force application to the breaking point and the number of tissue breaks.

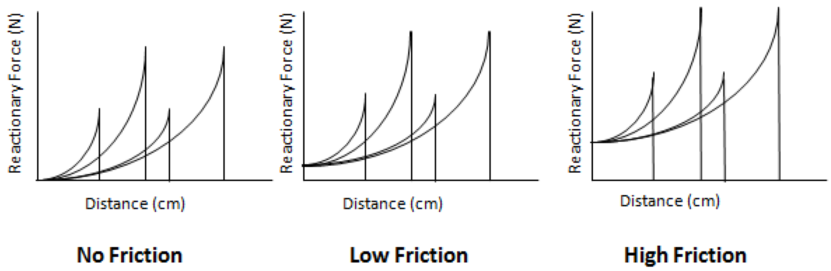

Figure 8. The four simulated material profiles and their respective actual break point locations used in the transfer-of-training phase.

Metrics for Analysis

1. Distance

Displacement traveled by the input device into the simulated materials was presented by the simulator in terms of millimeters, which ranged from 0 to 35 mm, with four values designed as breaking points at 7.5, 15, 22.5, and 30 (see Table 1).

2. Force

Reactionary force rendered by the simulator was presented as rendered voltage and transformed into Newtons, both of which are displayed in Table 1. Two voltages will define the reactionary behavior by the simulator: 3 and 5. The simulator will directly record voltage, which is then transformed into Newtons (see Table 1).

Table 1

Distance and reactionary force qualities at material break point defining each simulated profile

Material Profile	**Distance – all friction levels** *Millimeters*	**Reactionary force – no friction** *Newtons*	**Reactionary force – low friction** *Newtons*	**Reactionary force - high friction** *Newtons*
1	7.5	3	4.5	6
2	15	5	6.5	8
3	22.5	3	4.5	6
4	30	5	6.5	8

3. Accuracy

Accuracy will be defined as the difference between the participants' indicated break point location and the actual break point location of the simulated material profiles. When presented with materials that do not truly break, as in Task 1, the difference could be positive, indicating over application of force, or negative, indicating under application of force. When presented with materials that truly break with excessive force application, as in Task 2, accuracy will only be negative since estimates must be short of the true break location.

Results

Data were screened for outliers and for logging errors with the simulator. Due to the restricted range of motion of the simulator, no trials exceeded a z-value of ± 3, so no trials were excluded as outliers. However, 20 pretest trials and 27 posttest trials in the experimental condition, as well as 20 pretest trials and 20 posttest trials in the control condition, were not correctly recorded, with all values logged as 0 and were discarded.

Performance was assessed by analyzing displacement into the simulated material via distance in millimeters. Means and standard deviations of distance are displayed by material type in the experimental condition in Tables 2a, 2b, and 2c. Break point estimates from the pretest and posttest, averaged across all participants in the experimental group are also displayed in Figures 9 and 10.

Table 2a

Average break point distance estimate means and standard deviations (mm) by profile type in experimental condition with no friction

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	24.7	12.7	13.4	8.9	15.1	9.5	13.4	10.1
2	**15**	24.3	9.6	14.9	2.8	15.1	2.2	14.4	3.6
3	**22.5**	30.8	6.8	23.8	3.5	24.2	4.7	24.5	5.7
4	**30**	31.2	5.3	NA	NA	27.5	3.8	27.5	2.2

Table 2b

Average break point distance estimate means and standard deviations (mm) by profile type in experimental condition with low friction (1.5N)

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	22.5	12.8	10.1	5.4	8.6	3.2	11.9	8.8
2	**15**	21.5	8.3	14.3	2.9	13.5	1.9	13.8	2.3
3	**22.5**	28.1	7.6	22.4	2.9	21	4.6	22.6	4.4
4	**30**	28.8	6.9	NA	NA	26.1	4.8	26.5	2.4

Table 2c

Average break point distance estimate means and standard deviations (mm) by profile type in experimental condition with high friction (3N)

Material Profile	Actual Break Distance	Pre		Feedback		Post		Transfer	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	22.7	12.6	NA	NA	8.2	3	9.5	6.7
2	**15**	21.3	8.7	NA	NA	13.3	3.3	13.3	0.8
3	**22.5**	28.2	8.2	NA	NA	19.8	4.6	20	5.6
4	**30**	29	7.1	NA	NA	23	7.9	24.8	4.3

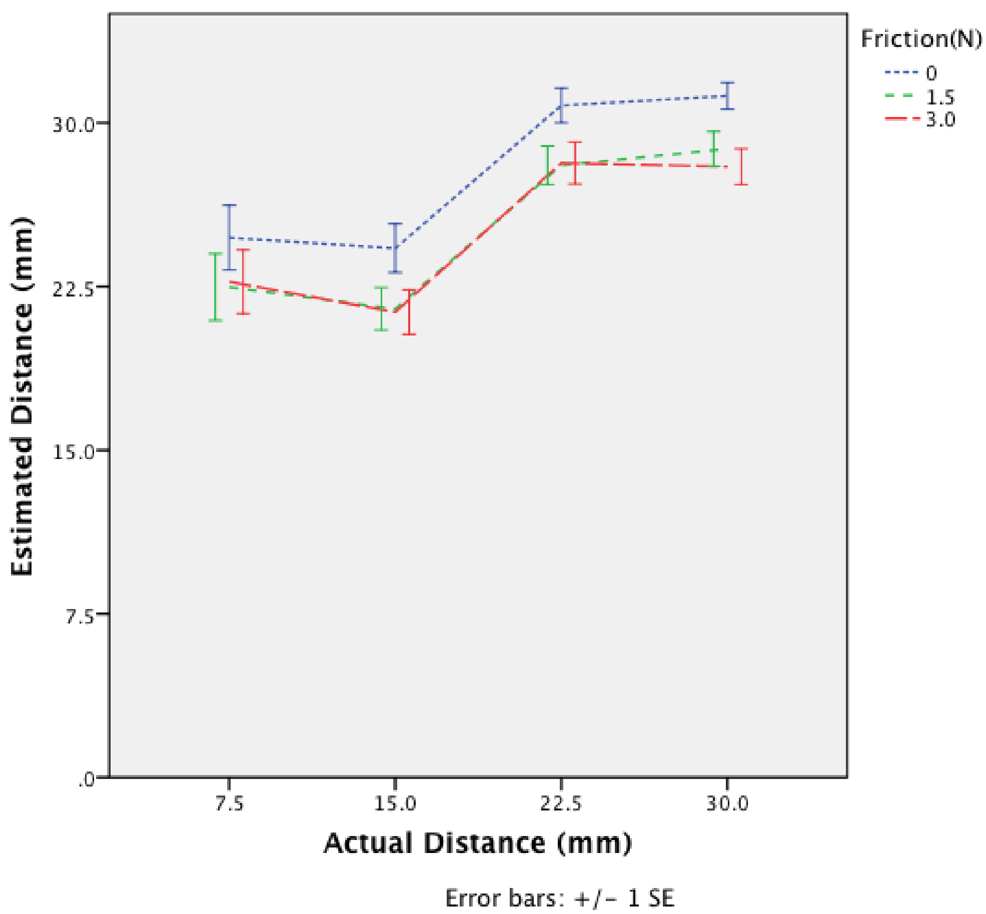

Figure 9. Average pretest break point estimates as a function of actual break point for all participants in the experimental condition.

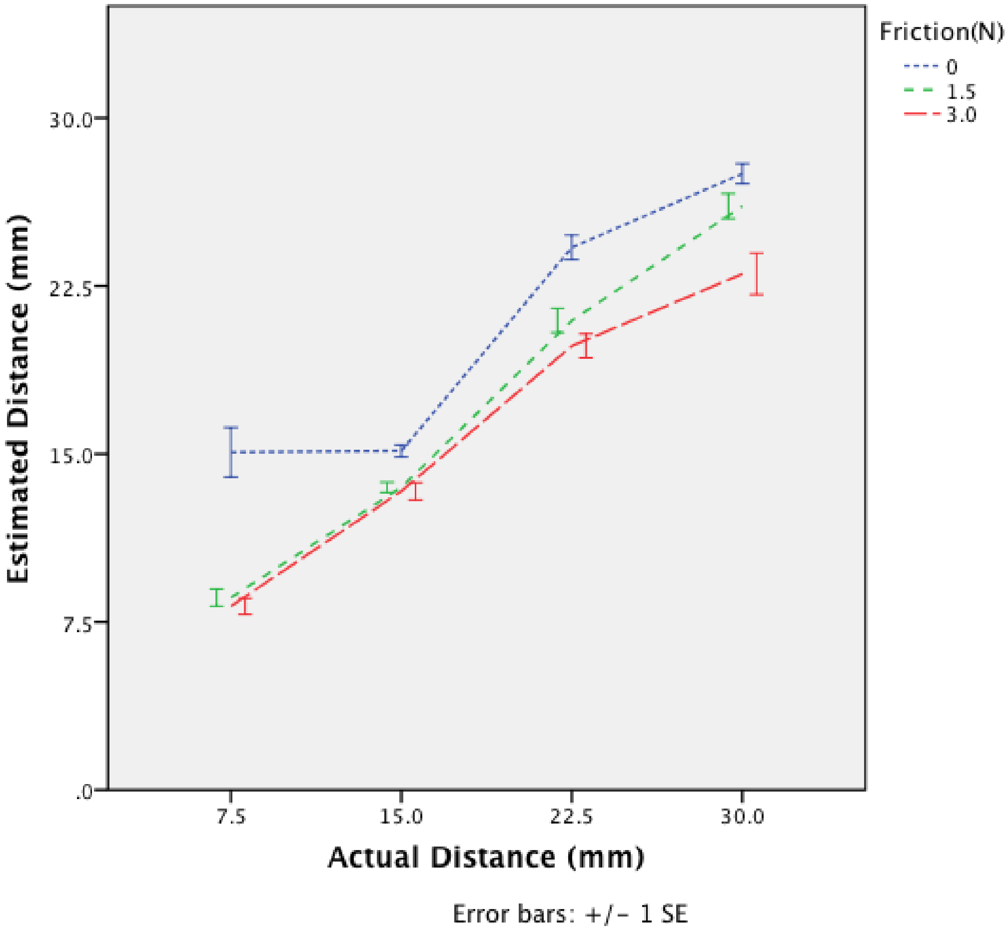

Figure 10. Average posttest break point estimates as a function of actual break point for all participants in the experimental condition.

Means and standard deviations of distance are displayed by material type in the control condition in Tables 3a, 3b, and 3c. Break point estimates from the pretest and posttest, averaged across all participants in the experimental group are also displayed in Figures 13 and 14.

Table 3a

Average break point distance estimate means and standard deviations (mm) by profile type in control condition with no friction

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	25.6	11.4	20.1	10.9	20.7	10.2	6.8	0.5
2	**15**	21.3	8	21.7	7.6	20.9	7.2	13.4	0.8
3	**22.5**	28.9	7	28.7	5.5	27.8	5.8	20.6	2.1
4	**30**	31	4.6	NA	NA	29.7	3.8	26.2	3

Table 3b

Average break point distance estimate means and standard deviations (mm) by profile type in control condition with low friction (1.5N)

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	20.6	11.1	19.2	10	16.6	9.6	6.8	0.6
2	**15**	20	7.4	19.8	7.1	18.7	5.8	13.1	1.5
3	**22.5**	27.8	6.4	27.1	6	26.2	5.8	19.8	3.1
4	**30**	28.6	6.6	NA	NA	28.1	5.4	25.3	3.9

Table 3c

Average break point distance estimate means and standard deviations (mm) by profile type in control condition with high friction (3N)

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	18.6	10.6	NA	NA	15.2	9.4	6.6	1
2	**15**	18.7	7.9	NA	NA	17.5	7.1	13	1
3	**22.5**	24.4	7.6	NA	NA	21.8	7.9	18.9	3.8
4	**30**	25.2	8.3	NA	NA	25.1	6.7	22.5	6

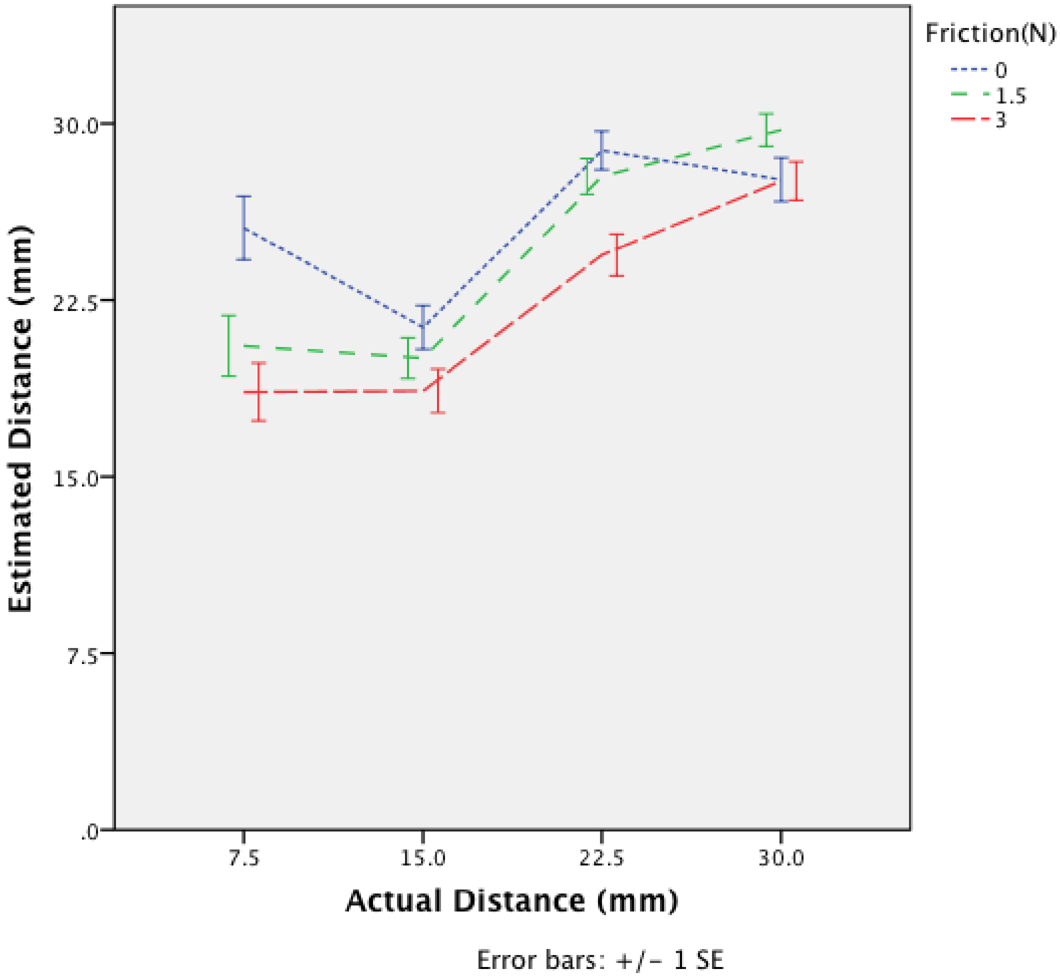

Figure 11. Average pretest break point estimates as a function of actual break point for all participants in the control condition.

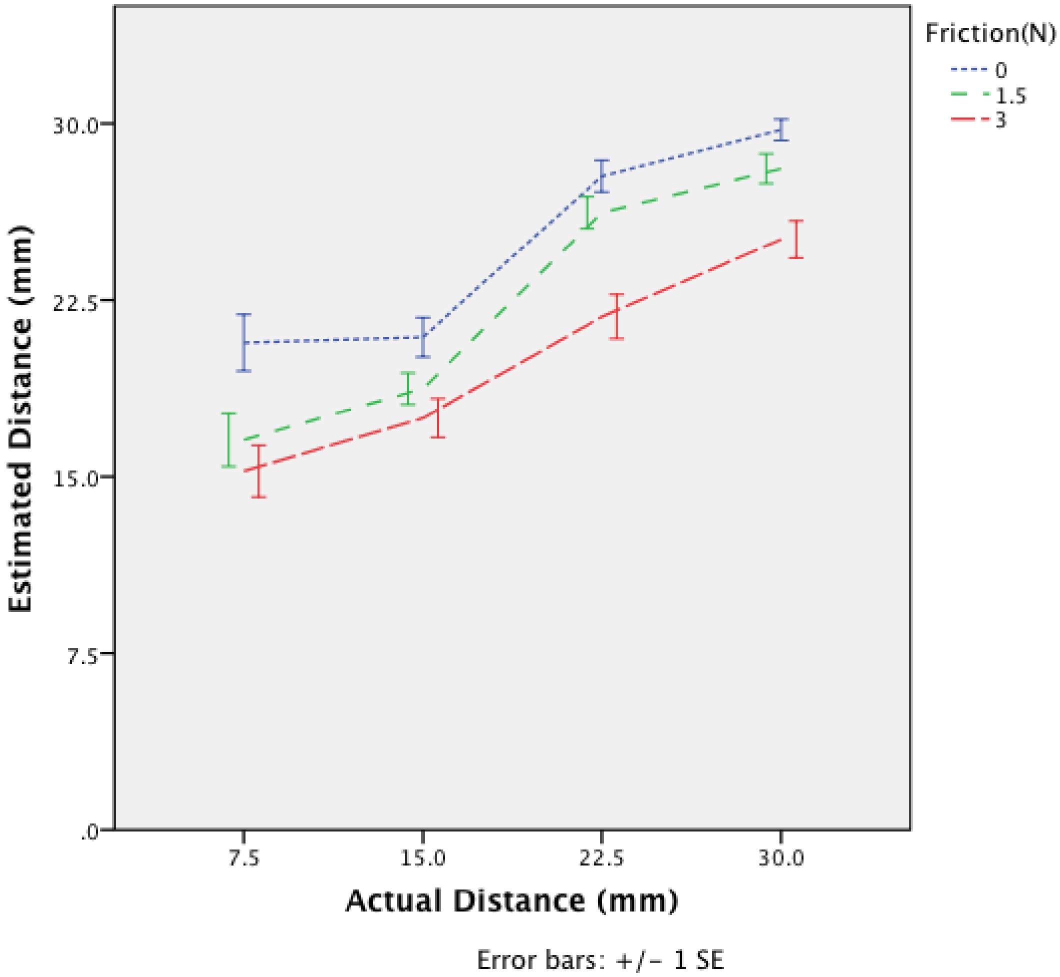

Figure 12. Average posttest break point estimates as a function of actual break point for all participants in the control condition.

Simple regression models were used to determine the slopes and intercepts of the functions predicting indicated distance from actual break point distance for each participant and for each experimental phase. Then, they are used for the comparisons of the contributors to perceptual estimates of distance of actual target distance and actual force. Slopes, intercepts, and R^2 values for both metrics for each participant across phases are displayed in Tables 4a, 4b, 4c, and 4d for those in the experimental condition, and Tables 5a, 5b, 5c, and 5d for those in the control condition. Perfect performance estimating break point would result in a $R^2 = 1$, slope = 1, and intercept = 0 for actual distance and $R^2 = 0$ for actual force. Slopes and intercepts given by regression techniques are more useful than other descriptive statistics such as session means and signed error because they describe the function that takes you from the actual target distances to the perceived target distances. Trials in which participants broke the material were excluded from analyses in the ToT Task, presented in Tables 4d and 5d, as the sudden decrease of reactionary force would cause the participant's estimate to fall close to or at the end of the physical limitations of the simulator.

Table 4a

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Pretest Phase for Each Participant in the Experimental Condition

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.082	-.09	39.2	.038	.07	35.2	.009	.04	35.5
2	.594	.65	18.8	.184	-.28	34.4	.159	-.44	28.4
3	.168	.28	27.4	.000	.004	34.6	.014	-.04	35.5
4	.434	.43	22.2	.408	-.82	36.07	.099	-.25	29.1
5	.000	.007	32.8	.817	.73	5.9	.324	-.2	40.9
6	.207	-.18	39.2	.108	.25	21.6	.407	.41	15.2
7	.116	-.13	38.7	.088	.17	32.5	.003	-.02	35.8
8	.897	1.02	-.2	.686	.69	5	.963	.8	1.3
9	.162	.35	14.7	.983	.84	1.3	.794	.58	6.4
10	.209	-.4	38.4	.478	-.25	38.4	.345	-.26	39.7
11	.249	.49	16.5	.109	.21	22.7	.000	-.001	25.7
12	.148	-.28	29.8	.019	.1	25.2	.42	.57	14.8
13	.262	.5	16.6	.104	.28	10.1	.464	.59	4.6
14	.984	.92	.8	.976	.9	1.3	.992	.95	-.2
15	.843	.7	8	.979	.9	.9	.616	.7	2
16	.000	.004	37.9	.002	.02	33.2	.223	-.17	37.8
17	.066	-.17	37.3	.412	.57	10.5	.07	.27	21.4
18	.392	.38	25	.425	.56	19.5	.243	.49	18.4
19	.303	.49	17.3	.389	.5	21	.257	.49	13.2
20	.991	.89	0	.994	.89	1.2	.96	.86	2.2
21	.981	.91	.9	.978	.85	1.2	.416	.47	11.1
22	.25	.5	9.8	.998	1.02	-.3	.987	1	-.4
24	.008	.04	34.5	.148	-.28	37.4	.001	.009	35.4
25	.072	.16	29.5	.000	.01	29.7	.005	-.05	26.5
31	.908	1.08	-.8	.925	1.08	-.9	.614	.62	6.3
Avg	**.373**	**.34**	**21.4**	**.450**	**.36**	**18.3**	**.375**	**.3**	**19.5**

Table 4b

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Feedback Phase for Each Participant in the Experimental Condition

	Friction 1			Friction 2		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.004	-.06	27.7	.459	.45	11.9
2	.787	.81	4.4	.591	.62	7.9
3	.002	-.06	28	.864	.91	3.5
4	.002	.04	21	.517	.84	3.3
5	.768	.71	6.1	.331	.48	9.1
6	.89	1	.6	.975	.97	.7
7	.355	.56	8.3	.984	1	-1.1
8	.724	.84	3.1	.967	1	-.57
9	.165	.42	9.3	.62	.67	3
10	.957	1.1	-1	.055	.33	12.3
11	.457	.56	7.9	.871	.92	2
12	.458	.49	9.5	.887	.98	1.5
13	.973	1	-.67	.931	.97	-.6
14	.995	1.03	-.77	.98	.95	.07
15	.677	.69	7.1	.962	1.03	-1.87
16	.893	.75	4.16	.44	.81	3.65
17	.937	.95	.52	.89	.88	1.5
18	.87	.99	1.59	.859	1.09	.43
19	.064	.36	15.05	.089	.38	12.42
20	.136	.54	9.5	.975	.92	.69
21	.99	1.04	-.76	.981	.89	1.19
22	.981	.95	1.07	.991	.98	.22
24	.335	.59	7.71	.142	.39	10.4
25	.242	.79	6.84	.983	1	-.31
31	.882	1	0.5	.957	1.1	-1.5
Avg	**.582**	**.68**	**7.1**	**.732**	**.82**	**3.2**

Table 4c

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Posttest Phase for Each Participant in the Experimental Condition

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.712	.63	7.32	.083	.17	8.19	.203	-.18	11.64
2	.486	.55	12.39	.971	.9	1.09	.32	.58	1.16
3	.131	.29	25.74	.877	.81	6	.084	.25	8.05
4	.18	.24	11.87	.194	.36	12.11	.731	.76	5.07
5	.208	.37	16.5	.858	.7	5.37	.809	.89	-1.35
6	.278	.38	14.37	.902	.7	5.5	.923	.69	5.06
7	.292	.53	7.6	.555	.74	.16	.976	.86	.45
8	.031	.14	21.4	.984	.85	.73	.938	.82	.56
9	.811	.66	4.31	.997	.86	1.53	.117	.23	8.73
10	.964	.89	2.33	.764	.88	-.12	.989	.89	1.32
11	.969	.8	3.41	.493	.63	3.65	.607	.6	3.32
12	.052	.19	20.58	.991	.876	1.71	.712	.68	7.22
13	.108	.28	19.05	.988	.92	1.08	.995	.9	.23
14	.994	.92	.58	.995	.94	-.6	.977	.97	-1.95
15	.997	.92	.35	.991	.93	-.1	.955	.79	.98
16	.991	.84	2.67	.39	.53	3.55	.002	.03	10.09
17	.904	.94	2.64	.989	.86	.95	.996	.904	.433
18	.518	.55	7.53	.985	.9	.89	.599	.7	3.22
19	.213	.43	15.21	.961	2.3	.91	.902	.84	3.14
20	.998	.93	.45	.995	.93	0	.993	.88	.68
21	.995	.94	.2	.993	.92	.08	.683	.64	1.98
22	.99	.95	1.3	.995	.93	1.48	.992	.94	.72
24	.749	.67	10.05	.824	.85	1.88	.659	.42	11.9
25	.211	.42	14.79	.996	.95	-.04	.982	.96	.56
31	.995	.99	-.12	.995	.96	-.33	.95	.88	1.4
Avg	**.591**	**.62**	**8.9**	**.831**	**.86**	**2.23**	**.724**	**.68**	**3.38**

Table 4d

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the ToT Phase for Each Participant in the Experimental Condition

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.997	.92	-.01	.991	.94	-.4	.733	.78	.3
2	.991	.94	.03	.981	.85	1	.991	.84	1
3	.991	.95	-.1	.995	.9	.7	.275	.51	6
4	.359	.36	8	.9	.8	1.3	.432	.33	6.5
5	1.0	.95	-.3	.985	.9	.2	.934	.8	-.2
6	.994	.95	.1	.997	.95	.04	.918	.75	2.6
7	.932	.88	.3	.995	.87	.7	.991	.89	.6
8	.995	.9	.01	.987	.9	-.1	.834	.68	2.6
9	.991	.9	.7	.991	.84	1.2	.993	.78	1.6
10	.995	.92	.3	.962	.79	1.8	.994	.92	.01
11	.993	.91	.5	.999	.94	-.2	.983	.92	.07
12	.994	.95	.3	.996	.9	.6	.943	.87	.4
13	.997	.96	.2	.993	.92	-.03	.984	.88	.5
14	.997	.93	.4	.996	.93	.2	.996	.97	-1
15	.990	.92	-.4	.995	.88	.3	.985	.77	1.1
16	.997	.93	.3	.858	.76	1.4	.983	.86	.7
17	.996	.93	.2	.992	.83	.6	.624	.6	4.5
18	.995	.93	-.1	.620	.7	3.1	.990	.89	.6
19	.999	.95	-.08	.998	.92	.4	.997	.93	.2
20	.992	.91	.35	.995	.89	.2	.988	.86	7
21	.996	.96	-.5	.994	.9	.2	.971	.79	1.3
22	.999	.99	-.7	.996	.96	-.2	.998	.98	-.8
24	.988	.91	.5	.987	.86	.1	.997	.89	.07
25	.994	.95	-.5	.985	.92	-1.1	.978	.84	.7
31	.998	1	-.6	.994	.96	-.5	.998	.93	.04
Avg	**.967**	**.91**	**.4**	**.967**	**.88**	**.5**	**.900**	**.81**	**1.5**

Table 5a

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Pretest Phase for Each Participant in the Control Condition

	Friction 1			**Friction 2**			**Friction 3**		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
23	.041	.1	29.4	.147	.08	28	.088	-.39	30.7
26	.003	-.05	26.8	.309	.49	12.4	.000	.02	21.6
27	.051	.08	35	.119	-.09	37	.001	-.01	32.9
28	.018	-.13	27.2	.966	1.7	.86	.980	.92	-0.2
29	.110	-.11	38	.016	-.07	31	.464	.48	13.3
30	.025	-.1	35.7	.298	.53	11	.766	.48	9.4
32	.946	.9	4.2	.435	.61	7.2	.008	-.03	12.8
33	.617	.59	16.6	.428	.58	14.3	.805	.85	5.9
34	.164	.42	15.7	.483	.5	13.1	.965	.93	1
35	.001	-.02	33.4	.468	.47	11.9	.021	.09	15.1
36	.024	.12	28.3	.883	.88	3.1	.094	.09	28.5
37	.882	.89	5.6	.452	.66	13.5	.103	.29	6.6
38	.077	.35	21.3	.737	1.1	0.9	.980	.89	0.8
39	.150	.38	20.9	.666	.85	6.7	.935	.84	4.2
40	.784	.63	1.4	.106	.15	7.3	.002	.02	6.4
41	.247	.36	24.8	.275	.47	19.1	.153	.19	26.3
42	.616	.79	5.5	.002	-.03	35.8	.272	.41	17.6
43	.053	.13	28.3	.118	.18	25.8	.038	-.08	30.1
44	.334	.63	9.6	.981	.87	2.1	.922	.85	2.5
45	.950	.87	2.5	.874	.94	-0.1	.973	.99	0.3
46	.154	.25	23.1	.254	.26	25.8	.001	.02	25.9
48	.106	.24	26.9	.037	.03	34.1	.078	-.06	34.2
49	.101	.2	22.8	.041	.1	28.6	.290	.39	21.4
50	.006	.05	19.9	.008	.05	21.1	.081	-.22	28.7
52	.769	.73	7.6	.114	.25	14.7	.553	.74	6.1
Avg	**.289**	**.33**	**20.4**	**.369**	**.45**	**16.2**	**.383**	**35**	**15.3**

Table 5b

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Feedback Phase for Each Participant in the Control Condition

	Friction 1			**Friction 2**		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
23	.000	0	30.2	.003	.04	29.8
26	.959	.85	1.3	.283	.41	9.5
27	.191	.15	31.4	.125	.11	33.5
28	.784	.74	4.5	.396	.59	5.8
29	.821	1	1.8	.499	.7	8.8
30	.289	.38	25.5	.616	.58	21.9
32	.923	1.1	4.3	.861	.84	8
33	.561	.57	14	.966	.88	2.9
34	.318	9.91	.6	.462	.61	9.8
35	.379	.62	9.9	.735	.72	4.4
36	.985	.98	-.8	.818	.77	1.8
37	.825	1.13	.5	.891	1.1	2.4
38	.004	.06	32	.102	.55	13.5
39	.824	1	2.8	.907	1	.2
40	.871	.84	7.3	.843	.75	6.2
41	.004	.07	26.4	.112	.35	23.1
42	.294	.32	25.3	.01	27.2	.06
43	.269	.34	23.8	.039	.09	29.4
44	.776	1.3	-3.1	.762	1.2	-1.9
45	.012	-.14	33.1	.568	.84	7.6
46	.871	.68	16.1	.309	.448	9.6
48	.067	-.1	36.5	.022	.07	30.9
49	.167	.34	25.2	.269	.47	21.1
50	.983	.95	-1.1	.281	-.58	31.9
52	.138	.33	20.5	.515	.7	14.1
Avg	**.493**	**.94**	**14.7**	**.456**	**1.62**	**13**

Table 5c

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Posttest Phase for Each Participant in the Control Condition

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
23	.077	.17	26.2	.014	-.09	26.8	.026	.12	24.7
26	.858	.74	3.8	.988	.84	.5	.993	.89	-.3
27	.135	.1	27.8	.1	.07	24.7	.07	-.11	31.5
28	.056	.15	18.6	.994	.91	.1	.861	.69	2.3
29	.309	.5	15.1	.851	.94	2.1	.215	.41	9.1
30	.252	.23	25.1	.001	.02	24.1	.118	-.25	25.6
32	.774	.78	10.8	.93	1	7	.967	.92	5.9
33	.961	.92	3.3	.968	.96	1.2	.958	.96	-.89
34	.359	.45	13.5	.899	.62	6.2	.084	.17	10.2
35	.903	.91	1.8	.885	.83	.2	.794	.59	6.8
36	.553	.69	7.6	.986	.89	.2	.992	.85	1
37	.408	.45	21.6	.867	.96	6.3	.014	-.099	18.3
38	.219	-.14	36.2	.000	.01	28.4	.994	.92	.4
39	.295	.54	11.2	.984	.14	1	.410	.79	-1.9
40	.98	.79	8.5	.955	.88	6.2	.577	.84	4.7
41	.000	.001	26.7	.416	.54	17.7	.392	.5	21.5
42	.011	.04	29.7	.624	.38	21.5	.56	.49	11.4
43	.528	.22	29.1	.056	.11	31.5	.009	-.04	32.1
44	.334	.62	9.5	.992	.93	-.4	.985	.97	-1.2
45	.327	.45	19	.792	.73	10.2	.646	.58	2.5
46	.262	.41	11.5	.01	.05	19.3	.128	-.11	15.8
48	.002	-.02	32.3	.106	.11	27.1	.063	-.06	32.8
49	.390	.38	22.3	.059	.19	22.9	.482	.37	16.1
50	.994	.91	-1	.99	.87	-.7	.940	.73	1.1
52	.516	.7	6.6	.030	.11	18.5	.55	.24	13.5
Avg	**.420**	**.44**	**16.7**	**.58**	**.52**	**12.1**	**.513**	**.45**	**11.3**

Table 5d

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the ToT Phase for Each Participant in the Control Condition

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
23	.996	.93	.2	.993	.94	-.3	.382	.43	6.7
26	.992	.91	-.6	.991	.8	1	.968	.82	.9
27	.957	.77	2.5	.797	.62	3.2	.294	.22	7.3
28	.987	.91	.2	.976	.84	1.3	.975	.86	.6
29	.977	.88	.5	.884	.83	0	.993	.91	-.06
30	.996	.94	-.3	.995	.9	.4	.978	.9	.4
32	.995	.93	.3	.995	.89	.4	.990	.9	.4
33	.991	.89	1.7	.996	.96	-.5	.988	.87	.5
34	.997	.86	.9	.994	.88	.6	.978	.8	1.9
35	.837	.66	1	.300	.35	3.7	.486	.31	3.8
36	.995	.93	.1	.986	.9	.3	.990	.9	-.3
37	.991	.91	.7	.935	.87	.1	.987	.92	-.2
38	.996	.91	.3	.991	.93	-.2	.992	.91	.5
39	.997	.93	.3	.999	.992	-.5	.995	.92	.2
40	.967	.92	-1.2	.981	.87	.9	.320	.45	3.7
41	.833	.58	4.9	.604	.85	-2.3	.490	.36	6.4
42	.997	.98	-.7	.994	.94	.1	.698	.51	7.8
43	.991	1.09	-3.9	.982	.88	.7	.813	.6	4.3
44	.994	.87	.6	.947	.79	.7	.978	.97	-2.4
45	.991	.91	-.1	.996	.94	-.2	.358	.49	3.9
46	.464	.55	4.1	.754	.62	2.6	.759	.5	5
48	.995	.89	.3	.986	.88	.7	.988	.9	.2
49	.992	.83	1.3	.814	.71	3	.715	.65	2.9
50	.994	.94	-.8	.985	.83	.1	.974	.76	.3
52	.988	.82	.9	.939	.77	1.3	.539	.56	3.5
Avg	**.956**	**.87**	**0.5**	**.913**	**.83**	**.7**	**.785**	**.7**	**2.3**

Comparing Experimental & Control Conditions

Pretest. Examination of Tables 4a-d and 5a-d reveals that across friction levels, the R^2 values did not differ between the experimental and control conditions during the pretest. A 3x2 mixed ANOVA using the R^2 values from both conditions in the pretest confirmed that there was no statistically significant difference in R^2 values during pretest performance, $F(1, 48) = .413$, $p = .523$. There also were no significant effect in the difference in R^2 values of break point estimates for different friction levels $F(2, 96) = 1.139$, $p = .319$, or significant condition by friction interaction, $F(2, 96) = .495$, $p = .585$.

Similarly, slope values did not differ between the experimental and control conditions in the pretest. A 3x2 mixed ANOVA using slope values from both conditions in the pretest confirmed no significant differences during pretest performance, $F(1, 48) = .237$, $p = .629$. There also was no effect of friction on break point estimates across participants $F(2, 96) = 1.24$, $p = .291$, or significant condition by friction interaction, $F(2, 96) = .426$, $p = .626$.

Similar to findings from R^2 values and slope, intercept values observed in simple regressions of individual participant performance did not differ between the experimental and control conditions in the pretest. A 3x2 mixed ANOVA using intercept values from both conditions in the pretest confirmed no significant differences during pretest performance, $F(1, 48) = .538$, $p = .467$. However, there was an effect of friction across the different friction levels $F(2, 96) = 3.915$, $p = .023$, but no significant condition by friction interaction, $F(2, 96) = .613$, $p = .544$. Follow up paired samples t-tests revealed that there were no significant differences in intercept values of simple regressions of break point estimates between friction levels during the pretest within the experimental condition. However, the change in R^2 values in the control condition for materials with no friction (M = .591, SD = .38) compared to low friction of 1.5N (M = .831, SD = .27) revealed a significant difference between the estimates in the two friction levels, $t(24) = -2.557$, $p = .017$.

Posttest. A 3x2 mixed ANOVA using the R^2 values from both conditions in the posttest phase revealed a significant effect of condition $F(1, 48) = 7.97$, $p < .01$ indicating that those who experienced the intervening calibration session tended to produce break point estimates more strongly based on the actual break point. There was also a main effect of friction level $F(2, 96) = 5.893$, $p < .01$, but no condition by friction interaction $F(2, 96) = .234$, $p = .792$. Follow up paired samples t-tests revealed that there were no significant differences in R^2 values of break point estimates between friction levels during the posttest within the control condition. However, the increase in R^2 values in the experimental condition for materials with no friction (M = .591, SD = .38) compared to low friction of 1.5N (M = .831, SD = .27) revealed a significant difference between the estimates in the two friction levels, $t(24) = -2.557$, $p = .017$.

A 3x2 mixed ANOVA of the slope values observed during posttest performance for each participant revealed a significant effect of condition $F(1, 48) = 10.48$, $p < .01$ indicating that those who experienced the intervening calibration session tended to produce simple regressions with a slope closer to 1. There was also a main effect of friction level $F(2, 96) = 4.73$, $p < .05$, but no condition by friction interaction $F(2, 96) = 1.12$, $p = .329$. Follow up paired samples t-tests revealed that there were no significant differences in break point estimates between friction levels during the posttest within the control condition. However, the increase in slope values in the experimental condition for materials with no friction (M = .62, SD = .28) compared to low friction of 1.5N (M = .86, SD = .36) revealed a significant difference between the estimates in the two friction levels, $t(24) = -2.618$, $p = .015$, as did the increase in slope values from materials with high friction of 3N (M = .67, SD = .3) to low friction of 1.5N (M = .86, SD = .36), $t(24) = 2.487$, $p = .02$.

A 3x2 mixed ANOVA of the intercept values observed during posttest performance for each participant revealed a significant effect of condition $F(1, 48) = 15.757$, $p < .001$ indicating that those who experienced the intervening calibration session tended to produce simple regressions with an intercept closer to 0. There was also a main effect of friction level $F(2, 96) = 18.667$, $p < .001$, but no condition by friction interaction $F(2, 96) = .628$, $p = .536$. Follow up paired samples t-tests revealed significant differences in break point estimates between friction levels during the posttest within the control condition between materials with no friction (M = 16.7, SD = 10.6) and low friction of 1.5N (M = 12.1, SD = 11.3) $t(24) = 3.367$, $p = .003$, as well as no friction (M = 16.7, SD = 10.6) and high friction of 3 N (M = 11.3, SD = 11.3) $t(24) = 2.871$, $p = .008$. Within the experimental condition, intercept values also differed between materials with no friction (M = 8.9, SD = 7.8) and low friction of 1.5N (M = 2.2, SD = 3.1) $t(24) = 4.494$, $p < .0001$, and between materials with no friction (M = 8.9, SD = 7.8) and high friction of 3N (M = 3.4, SD = 4), $t(24) = 3.347$, $p = .003$. The R^2 values and the slopes of the simple regressions tended to increase in the experimental group compared to the control group, moving more closely to 1.0, and the intercepts decreased, moving more closely to 0.

Comparing Pretest and Posttest Phases

Control Condition. Examination of Tables 4a-d and 5a-d reveals that across friction levels, the R^2 values differed across phases in the control condition. A 3x2 repeated measures ANOVA using the R^2 values from both phases in the control condition confirmed that the R^2 values during pretest performance (M = .347, SE = .05) were significantly lower than during posttest performance (M = .504, SE = .062) $F(1, 24) = 5.536$, $p < .05$. There was, however, no significant effect in the difference in R^2 values of break point estimates for different friction levels $F(2, 48) = 1.888$, $p = .162$, or significant phase by friction interaction, $F(2, 48) = .434$, $p = .651$.

Slope values did not differ across phases in the control condition. A 3x2 repeated measures ANOVA using slope values from both phases in the control condition confirmed no significant differences across phase, $F(1, 24) = 1.564$, $p = .223$. There also was no effect of friction on break point estimates across participants $F(2, 48) = 1.24$, $p = .291$, or significant phase by friction interaction, $F(2, 48) = 1.637$, $p = .205$.

Similar to findings from slope values, intercept values observed in simple regressions of individual participant performance did not differ across phases in the control condition. A 3x2 repeated measures ANOVA using intercept values from both phases in the control condition confirmed no significant differences across phase, $F(1, 24) = 4.228$, $p = .051$. However, there was an effect of friction across the different friction levels $F(2, 48) = 6.904$, $p < .05$, but no significant phase by friction interaction,

$F(2, 48) = .01$, $p = .99$. Follow up paired samples t-tests revealed that there were significant differences in intercept values of simple regressions of break point estimates between friction levels of no friction (M = 18.55, SD = 10.93) and low friction of 1.5N (M = 14.16, SD = 11.59), $t(49) = 3.005$, $p < .05$. There were also significant differences in estimates between materials with no friction (M = 18.55, SD = 10.93) and high friction of 3N (M = 13.3, SD = 11.62), $t(49) = 3.556$, $p < .05$. However, there were no differences in estimates between materials with low friction (M = 14.16, SD = 11.59) and high friction (M = 13.3, SD = 11.62), $t(49) = .732$, $p = .468$.

Experimental Condition. A 3x2 repeated measures ANOVA using the R^2 values from both phases in the experimental condition confirmed that the R^2 values during pretest performance (M = .399, SE = .065) were significantly lower than during posttest performance (M = .715, SE = .041) $F(2, 24) = 41.081$, $p < .05$. There was also a significant effect for different friction levels $F(2, 48) = 4.779$, $p < .05$, but no significant phase by friction interaction, $F(2, 48) = 1.26$, $p = .293$. Follow-up paired samples t-tests revealed significant differences between estimates of break points on materials with no friction (M = .482, SD = .38) and low friction of 1.5N (M = .64, SD = .39), $t(49) = -2.784$, $p < .05$, as well as between materials with low friction of 1.5N (M = .64, SD = .39) and high friction of 3N (M = .55, SD = .38), $t(49) = 2.21$, $p < .05$.

Slope values also differed across phases in the control condition. A 3x2 repeated measures ANOVA using slope values from both phases in the experimental condition revealed that slopes were steeper in the posttest (M = .33, SE = .08) than the pretest (M = .72, SD = .04), $F(1, 24) = 33.608$, $p < .05$. There was no effect of friction on break point estimates across participants $F(2, 48) = .282$, $p = .052$, or significant phase by friction interaction, $F(2, 48) = 1.827$, $p = .172$.

A 3x2 repeated measures ANOVA using intercept values from both phases in the experimental condition confirmed intercepts were significantly lower in the posttest (M = 4.84, SD = .74) than the pretest (M = 19.71, SD = 1.81), $F(1, 24) = 39.024$, $p < .05$. There was also an effect of friction across the different friction levels $F(2, 48) = 10.331$, $p < .05$, but no significant phase by friction interaction, $F(2, 48) = 1.508$, $p = .232$. Follow up paired samples t-tests revealed that there were significant differences in intercept values of simple regressions of break point estimates between friction levels of no friction (M = 15.14, SD = 13.05) and low friction of 1.5N (M = 10.27, SD = 13.27), $t(49) = 3.773$, $p < .05$. There were also significant differences in estimates between materials with no friction (M = 15.14, SD = 13.05) and high friction of 3N (M = 11.42, SD = 13.21), $t(49) = 3.012$, $p < .05$. However, there were no differences in estimates between materials with low friction (M = 10.27, SD = 13.27) and high friction (M = 11.42, SD = 13.21), $t(49) = -1.217$, $p = .229$.

In short, the results revealed an increase in the R^2 values and improvements in both slope and intercept, indicating a calibration effect that is characterized by an improved scaling of the estimates to the actual target break point distances. Similar improvements were seen in the control condition, but with smaller F-values than seen in the experimental condition. Next, multilevel modeling techniques were used to determine if the slopes and intercepts differed between the pretest and posttest sessions within each of the conditions.

Multilevel Modeling

Due to the repeated measurements of the same participants, the trials of estimates of break points are nested, or grouped, within participants. Variation in estimates may be affected by individual differences, which affect performance throughout all of a participant's estimates. Nested data structures violate assumptions for performing an ordinary least squares regression or repeated-measures ANOVA (Bickel, 2007). Therefore, multilevel modeling (MLM) was used to analyze the repeated measures model in order to account for the nesting, or grouping, of trials within participants, which allows for measurement occasions to be correlated. MLM accounts for correlated measurements by estimating error separately for measurement occasions, or trials, and for individuals.

In the following MLM analysis, a two-level hierarchical structure is employed, with each estimation trial defined as "Level 1" and each individual participant defined as "Level 2," allowing for the exploration of trial-level predictors, such as phase (pretest and posttest) and friction levels, and person-level predictors such as condition assigned (experimental versus control). The models employed were specified as:

$$Estimated\ Distance_{ti} = \beta_{0i} + \beta_{1i}(Actual\ Distance) + \beta_{2i}(Actual\ Force) + \beta_{3i}(Phase) + \beta_{4i}(Friction)$$

where $Estimated\ Distance_{ti}$, participant *i'*s estimated break point at trial *t*, is a function of an individual specific intercept parameter, β_{0i}; participant-specific slope parameters, β_{1i}, capturing actual break point distance, β_{2i}, capturing actual break point force, β_{3i}, representing which phase the estimate occurred in (pretest or posttest), and B_{4i}, representing the level of friction applied to the material. Models were used to analyze performance for the 25 participants in the experimental condition (N = 1753 trials), separately from the 25 participants in the control condition (N = 1760 trials). Separate models were then used to directly compare the two conditions.

It was important to first use an intercepts-only model without predictors to provide a baseline (or null) model for the individual-level dependent variable, estimated distance, and to determine if MLM was appropriate (Bickel, 2014). Results from the intercept-only model indicate an intraclass correlation (ICC) of .109 in the experimental condition, and .233 in the control condition, meaning that 11% and 23% of the total variance of break point estimates, respectively, resides between participants, and 89% and 77%, respectively, resides within participants, which supports the mixed model approach. It is recommended that MLM analyses be used if ICC values exceed 0.05 (Heck, Thomas, & Tabata, 2010).

Predictor variables were centered around the grand mean to allow for comparison of parameter estimates across models with both level-1 and level-2 predictors and to reduce possible effects of collinearity. Predictors were entered into the model hierarchically to determine their unique contribution to the model (see Tables 6 & 7).

Comparing Phases. Two models were analyzed, one for participants in each condition, experimental and control. Predictors were added to the model as fixed effects and random effects one at a time. If a predictor did not result in a significant effect, it was removed from the model. In the first model, estimated break point distance was entered as a dependent variable. Actual break point distance was entered as a fixed effect to determine the linear trend of break point estimates across actual break points and also entered as a random effect to determine the random error term. The final model included all predictors that resulted in significant fixed or random effects. All predictors produced significant fixed effects, and two produced significant random effects (actual distance and friction) in each model.

Experimental Condition. Although R^2 is not directly reported in MLM analyses by statistical software, a pseudo- R^2 was calculated, which represents the increase in explained variance (and thus the reduction in residual variance) contributed by the addition of a particular predictor. As seen in Table 6, actual break point distance, actual break point force, phase, and friction all resulted in significant fixed effects, with phase resulting in the greatest R^2 effect size of 24.9% reduction in error variance, followed by actual break point distance, 22.1%, friction, 4.3%, and actual force, 2.1%. As seen in Figures 13 and 14 and Tables 4a & 4c, break point estimates for all friction levels became more accurate in the posttest, with slopes becoming closer to 1 and intercepts becoming closer to 0. Although performance significantly improved after training, it appears that participants still tended to overestimate break point estimates for materials with low force values (Materials 1 & 3) and no friction, and underestimate break point estimates with high friction in the posttest. As evidenced in Figures 10 and 12 of posttest performance, it's possible the reactionary force in Material 1 fell below participants' perceptual threshold when no friction was applied, as performance still lagged after training. However, the introduction of friction, increasing the reactionary force as an operator probes on the tissue, may cause fragile materials such as Material 1 to become above perceptual threshold.

Table 6

Estimates of Fixed Effects and Standard Error (SE) in the Experimental Condition

Effect	Model 1 Estimate (SE)	Model 2 Estimate (SE)	Model 3 Estimate (SE)	Model 4 Estimate (SE)	Model 5 Estimate (SE)
Intercept	22.025 (.684)	22.007 (.685)	22.007 (.686)	17.982 (.7004)	17.989 (.701)
Actual Distance		.514 (.052)*	.586 (.116)*	.586 (.053)*	.586 (.053)*
Actual Force			-1.357 (.219)*	-1.367 (.179)*	-1.367 (.173)*
Phase				8.018 (.32)*	8.012 (.309)*
Friction					-1.185 (.213)*
Change in Model R^2	--	.221	.021	.249	.043

*$p < .05$

Calculations for Changes in Model R^2

- Model 2 (unique effect of actual distance)
  - Model 1 residual – model 2 residual / model 1 residual
  - (85.571 – 66.688) / 85.571 = .221
- Model 3 (unique effect of actual force)
  - Model 2 residual – model 3 residual / model 2 residual
  - (66.688 – 65.256) / 66.688 = .021
- Model 4 (unique effect of phase)
  - Model 3 intercept – model 4 intercept / model 3 intercept
  - (65.256 – 48.997) / 65.256 = .249
- Model 5 (unique effect of friction)
  - Model 4 intercept – model 5 intercept / model 4 intercept
  - (48.997 – 46.886) / 48.997 = .043

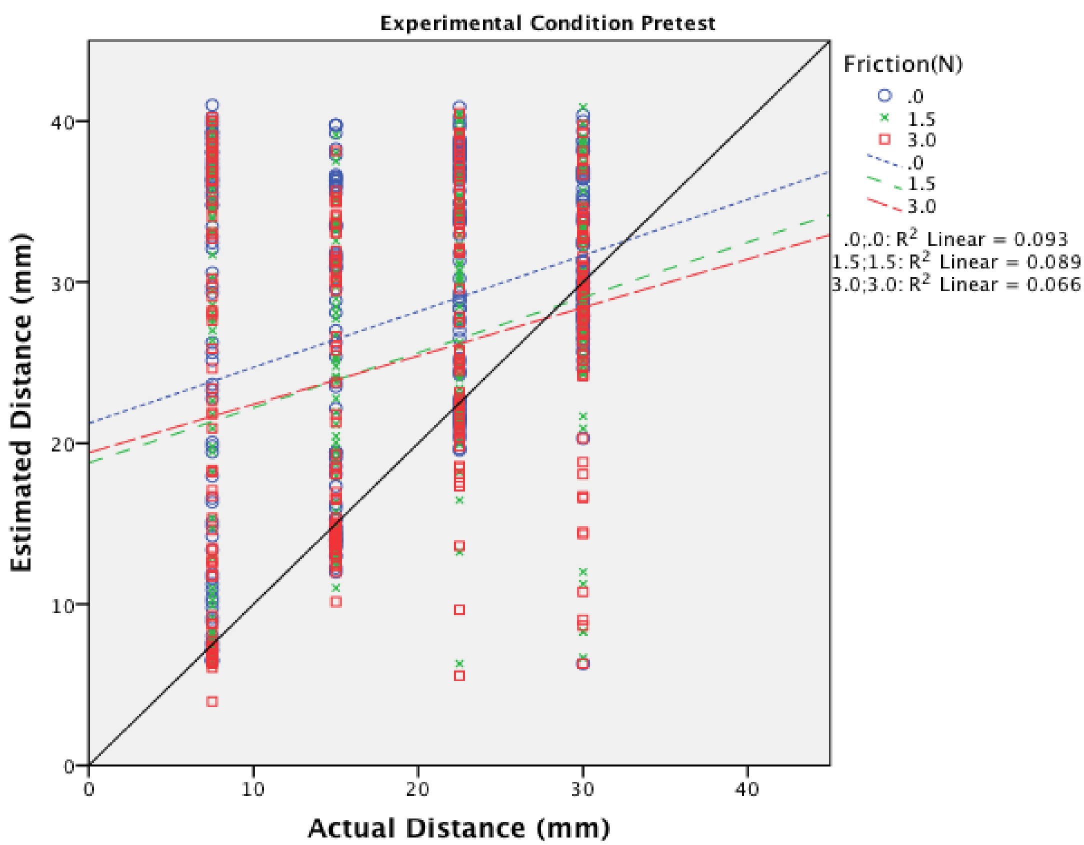

Figure 13. Pretest break point estimates as a function of actual break point for all participants in the experimental condition.

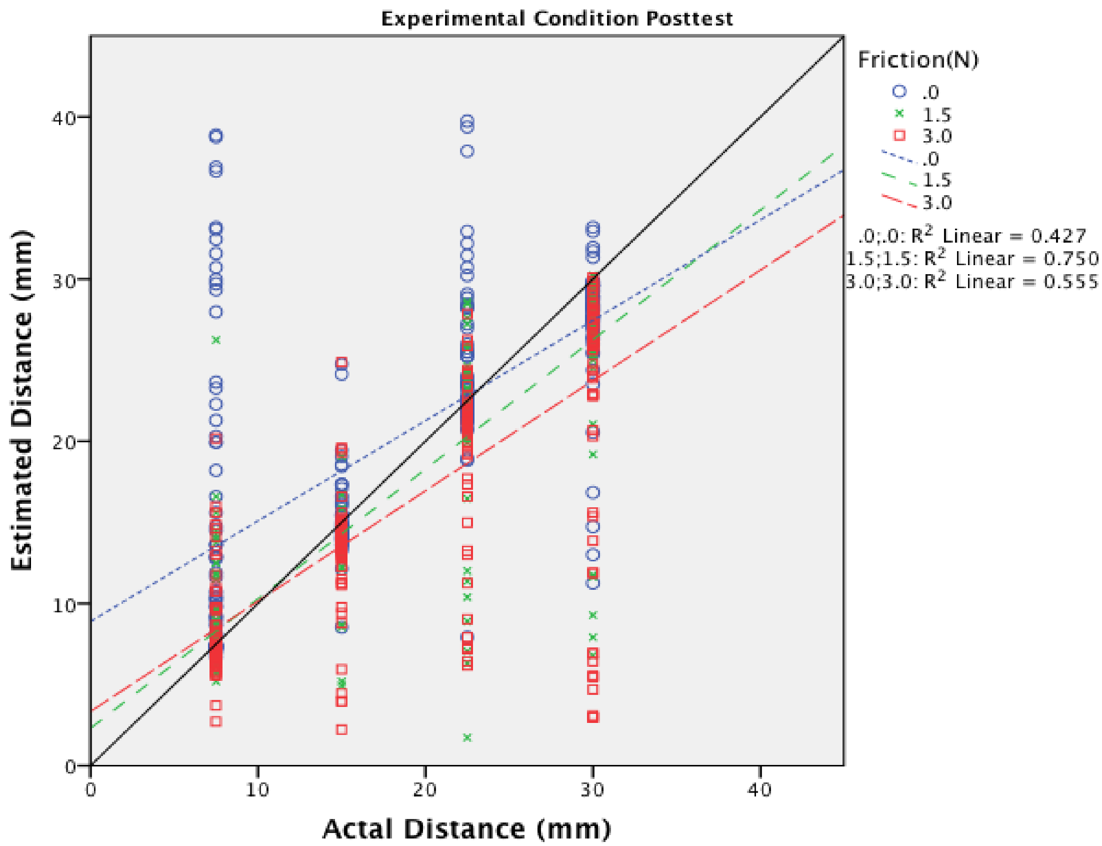

Figure 14. Posttest break point estimates as a function of actual break point for all participants in the experimental condition.

Random effects. The intercept variance for those in the experimental condition was estimated as 11.08, $p < .05$, so the estimate of the standard deviation is 3.33. This suggests that there are unmeasured predictor variables for each participant that raise or lower their performance. Individual participants will have intercepts that are within 3.33 mm higher or lower than the group average about 68% of the time, and within 6.66 mm higher or lower 95% of the time.

Significant random effects of slope also occurred for predictors Actual Distance and Friction (both *p*'s < .05). This suggests that the slope of actual distance predicting estimated distance and friction predicting estimated distance varies for each participant. Individual participant's estimates predicted by actual distance will have slopes that vary within $\pm$0.24 mm of the group average 68% of the time, and within $\pm$0.48 mm of the group average 95% of the time. Individual participant's estimates predicted by friction will also have slopes that vary within $\pm$0.86 mm steeper than the group average 68% of the time, and within $\pm$1.72 mm steeper than the group average 95% of the time. This simply suggests that some participants produced more accurate break point estimates than others, and some participants' were more successful than others in ignoring variations in friction level, with their estimates being less affected by the presence of friction.

Control Condition. As seen in Table 7, actual break point distance, actual break point force, phase, and friction all resulted in significant fixed effects, similar to the experimental condition. Although both conditions shared fixed and random effects, differences can be seen in effect sizes. For participants in the control condition who did not receive calibration training, actual break point distance resulted in the greatest R^2 effect size of 20.8% reduction in error variance, followed by friction, 8.6%, actual force, 3.5%, and phase, 1.7%. Although participants who did not receive training performed better in the posttest than the pretest, likely due to practice effects, the effect of phase accounted for only 1.7% of the variance compared to 24.9% in the experimental condition. As seen in Figures 13 & 14 and Tables 4a & 4c, break point estimates for all friction levels became somewhat more accurate in the posttest, with slopes becoming closer to 1 and intercepts becoming closer to 0.

Although friction was a significant fixed effect in both experimental and control group models, the R^2 was relatively small at 8.6% and 4.3% respectively, accounting for twice as much variance in the control group than the experimental group.

Table 7

Estimates of Fixed Effects and Standard Error (SE) in the Control Condition

Effect	Model 1 Estimate (SE)	Model 2 Estimate (SE)	Model 3 Estimate (SE)	Model 4 Estimate (SE)	Model 5 Estimate (SE)
Intercept	23.301 (.892)	23.318 (.893)	23.32 (.895)	22.411 (.909)	22.417 (.909)
Actual Distance		.427 (.02)*	.506 (.022)*	.506 (.022)*	.505 (.021)*
Actual Force			-1.468 (.184)*	-1.468 (.183)*	-1.461 (.175)*
Phase				1.818 (.327)*	1.815 (.313)*
Friction					-1.637 (.128)*
Change in Model R^2	--	.208	.035	.017	.086

*$p < .05$

Calculations for Changes in Model R^2

- Model 2 (unique effect of actual distance)
    - Model 1 residual – model 2 residual / model 1 residual
    - (62.573 - 49.573) / 62.573 = .208
- Model 3 (unique effect of actual force)
    - Model 2 residual – model 3 residual / model 2 residual
    - (49.573 – 47.848) / 49.573 = .035
- Model 4 (unique effect of phase)
    - Model 3 intercept – model 4 intercept / model 3 intercept
    - (47.848 - 47.037) / 47.848 = .017
- Model 5 (unique effect of friction)
    - Model 4 intercept – model 5 intercept / model 4 intercept
    - (47.037 - 43.001) / 47.037 = .086

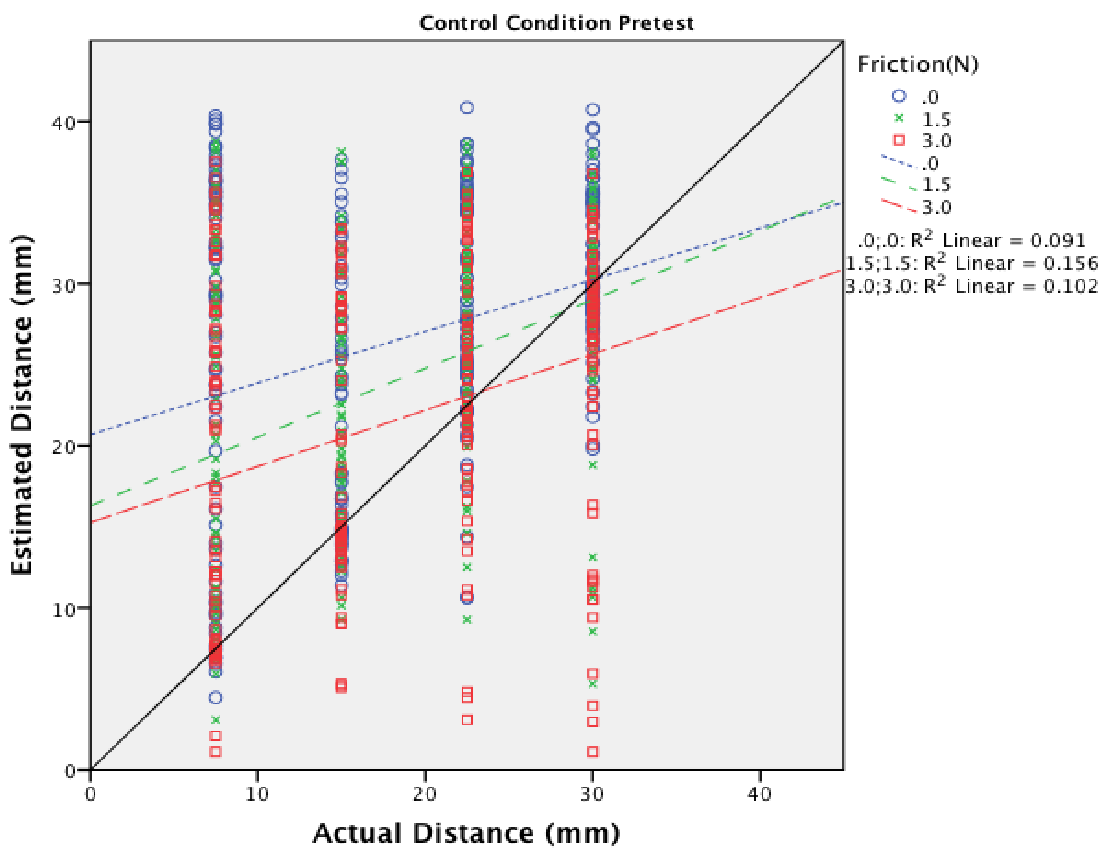

Figure 15. Pretest break point estimates as a function of actual break point for all participants in the control condition.

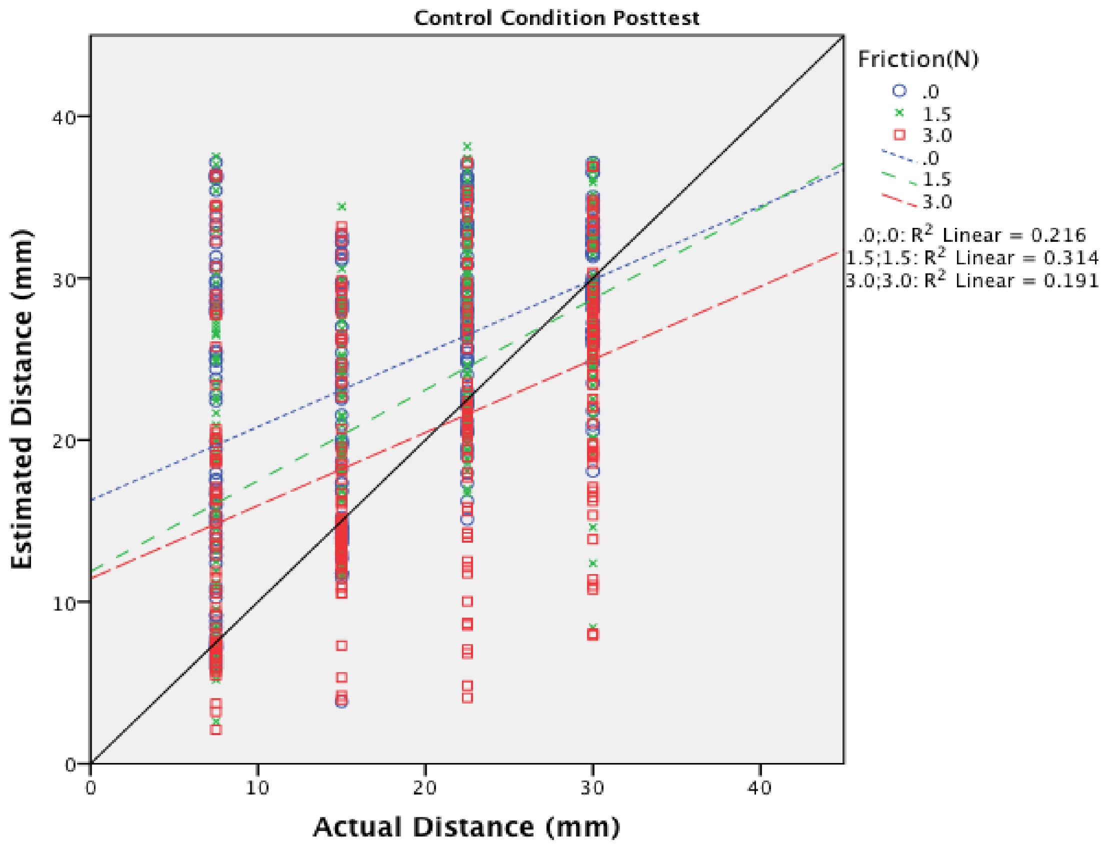

Figure 16. Posttest break point estimates as a function of actual break point for all participants in the control condition.

Random Effects. The intercept variance for those in the control condition was estimated as 19.54, $p < .05$, so the estimate of the standard deviation is 4.42. This suggests that there are unmeasured predictor variables for each participant that raise or lower their performance. Individual participants will have intercepts that are within 4.42 mm higher or lower than the group average about 68% of the time, and within 8.84 mm higher or lower 95% of the time.

Similar to the experimental condition, significant random effects of slope also occurred for predictors: Actual Distance and Friction, p's $< .05$. This suggests that the slope of actual distance predicting estimated distance and friction predicting estimated distance varies for each participant. Individual participant's estimates predicted by actual distance will have slopes that vary within ± 0.24 mm of the group average 68% of the time, and within ± 0.48 mm of the group average 95% of the time. Individual participant's estimates predicted by friction will also have slopes that vary within ± 1.24 mm of the group average 68% of the time, and within ± 2.48 mm of the group average 95% of the time, which was greater variance for Friction than observed in the experimental condition. This simply suggests that some participants produced more accurate break point estimates than others, and some participants' estimates were more affected by the presence of friction than others.

Comparing Conditions. Next, we consider if there was an effect of control versus experimental condition on break point estimates. Two models were conducted, one for pretest performance and one for posttest, with the same predictors as the final model for examining effect of phase, but replaced effect of phase with effect of Condition: Actual Distance, Actual Force, Friction, and Condition. As a Level 2 predictor, Condition was entered last into the model. There was a fixed effect of Condition in the posttest, $p < .05$, which reduced the error variance by 22.6%. Condition was not significant in the pretest, $p = .489$, indicating that there was no difference in participant performance in each group before training.

Transfer of Training Phase

The Transfer of Training task was more realistic than the previous three phases, in that materials would actually break if pushed past the simulated break point. As seen in Tables 4d and 5d, performance was very similar between the experimental and control conditions during the transfer of training phase, with those in the control group appearing to underestimate break points more than those in the experimental group. Number of breaks compared across friction level and material are displayed in Tables 8 & 9. Similar to Long et al. (2014), the majority of breaks occurred when materials required the lowest reactionary force before breaking (Materials 1 and 3). Breaks also appear to decrease as friction increases.

An independent samples t-test shows that the number of times a participant broke the tissue during the 36 trials in the experimental group (M = 4.64, SD = 3.09) was not significantly different than the number of times a participant broke the tissue in the control group (M = 4.36, SD = 2.8), $t(48) = 0.336$, $p < .05$. Although the number of tissue breaks did not differ between the groups, it's possible that combined with practice effects, those in the control group received enough haptic feedback within the first few trials to judge tissue break points as well as those in the experimental group. Future research should investigate different types of training (visual, haptic, or both) and the number of trials needed for calibration to occur.

Table 8

Break Frequency Occurrence in the ToT Phase Across Material and Friction Level for Participants in the Experimental Condition

Material	No Friction		Low Friction		High Friction		Total	
1	26/100	26%	27/96	28.1%	17/90	18.9%	**70/286**	**24.5%**
2	2/73	2.7%	2/75	2.7%	0/72	0%	**4/220**	**1.8%**
3	22/93	23.7%	16/86	18.6%	6/75	8%	**44/254**	**17.3%**
4	0/73	0%	0/75	0%	0/69	0%	**0/217**	**0%**
Total	**50/339**	**14.7%**	**45/332**	**13.6%**	**23/306**	**7.5%**	**118/977**	**12.1%**

Table 9

Break Frequency Occurrence in the ToT Phase Across Material and Friction Level for Participants in the Control Condition

Material	No Friction		Low Friction		High Friction		Total	
1	23/95	24.2%	21/90	23.3%	24/94	25.5%	**68/279**	**24.4%**
2	5/75	6.7%	6/80	7.5%	4/75	5.3%	**15/230**	**6.5%**
3	12/82	14.6%	14/87	16.1%	4/79	5.1%	**30/248**	**12.1%**
4	1/72	1.4%	1/73	1.4%	0/72	0%	**2/217**	**0.9%**
Total	**41/324**	**12.7%**	**42/330**	**12.7%**	**32/320**	**10%**	**115/974**	**11.8%**

CHAPTER THREE

EXPERIMENT TWO

Experiment 2 tested if the phenomenon of detecting material break points generalizes to a task other than pushing. The primary movements conducted during MIS procedures include pushing, pulling, sweeping, and grasping (Singapogu et al., 2012b). This experiment studied the generalizability of DTB to pulling motions, using the same methodologies and procedures as in Experiment 1, except that participants will be required to pull simulated tissues rather than push/probe them. If subjects can attune to the invariant of DTB, they should be able to attune to DTB in other tasks such as pulling, and results are expected to be the same as in Experiment 1.

Methods

Participants

23 university undergraduate students between the ages of 17 and 19 (M = 18.2, SD = 0.6) Participated in Experiment 2 after providing informed consent, none of whom had any experience practicing MIS. 12 were female and 11 were male. Participants received course credit in exchange for their participation.

Materials, Apparatus and Procedures

All materials and procedures were the same as in Experiment 1, except subjects were asked to pull simulated tissues using the laparoscopic device rather than push. The feedback training phase was completed two to ten days after the pretest phase (M = 7, SD = 2.2).

Results

Data were screened for outliers and for logging errors with the simulator. Due to the restricted range of motion of the simulator, no trials exceeded a z-value of ± 3, so no trials were excluded as outliers. However, two participants were excluded from the analyses because they could not complete the task. Also, 15 pretest trials and 19 posttest trials were not correctly recorded, with all values logged as 0, and were discarded.

Performance was assessed by analyzing displacement into the simulated material via distance in millimeters. Means and standard deviations of distance are displayed by material type and experimental phase in Tables 10a, 10b, and 10c. Break point estimates from the pretest and posttest, averaged across all participants in the experimental group are also displayed in Figures 17 and 18.

Table 10a

Average break point distance estimate means and standard deviations (mm) by profile type and experimental phase with no friction

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	19.8	10.7	12.8	7.2	13.6	6.6	6.9	0.4
2	**15**	20.2	7.7	16.5	4.6	16.8	3.8	13.6	0.7
3	**22.5**	26.5	6.6	23.2	4.2	24.1	4.1	20.8	1.3
4	**30**	28.1	5.5	NA	NA	28.7	3.6	26.6	2.6

Table 10b

Average break point distance estimate means and standard deviations (mm) by profile type and experimental phase with low friction (1.5N)

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	16.2	9.9	11.5	6.7	12.4	6.7	6.8	0.4
2	**15**	21.1	9	15.1	4.5	15.2	3.1	13.2	1.6
3	**22.5**	22.6	9.5	21	6.2	22.6	4.4	20.3	2.9
4	**30**	24.1	8	NA	NA	26.1	6.2	25.5	3.5

Table 10c

Average break point distance estimate means and standard deviations (mm) by profile type and experimental phase with high friction (3N)

Material Profile	**Actual Break Distance**	**Pre**		**Feedback**		**Post**		**Transfer**	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**7.5**	17.6	10.4	NA	NA	10.4	5.5	6.8	0.5
2	**15**	18.1	8.5	NA	NA	15	3.3	13.4	1
3	**22.5**	21.8	8.3	NA	NA	20.5	4.2	19.8	3.2
4	**30**	23	8.4	NA	NA	24.6	6.7	25.4	4

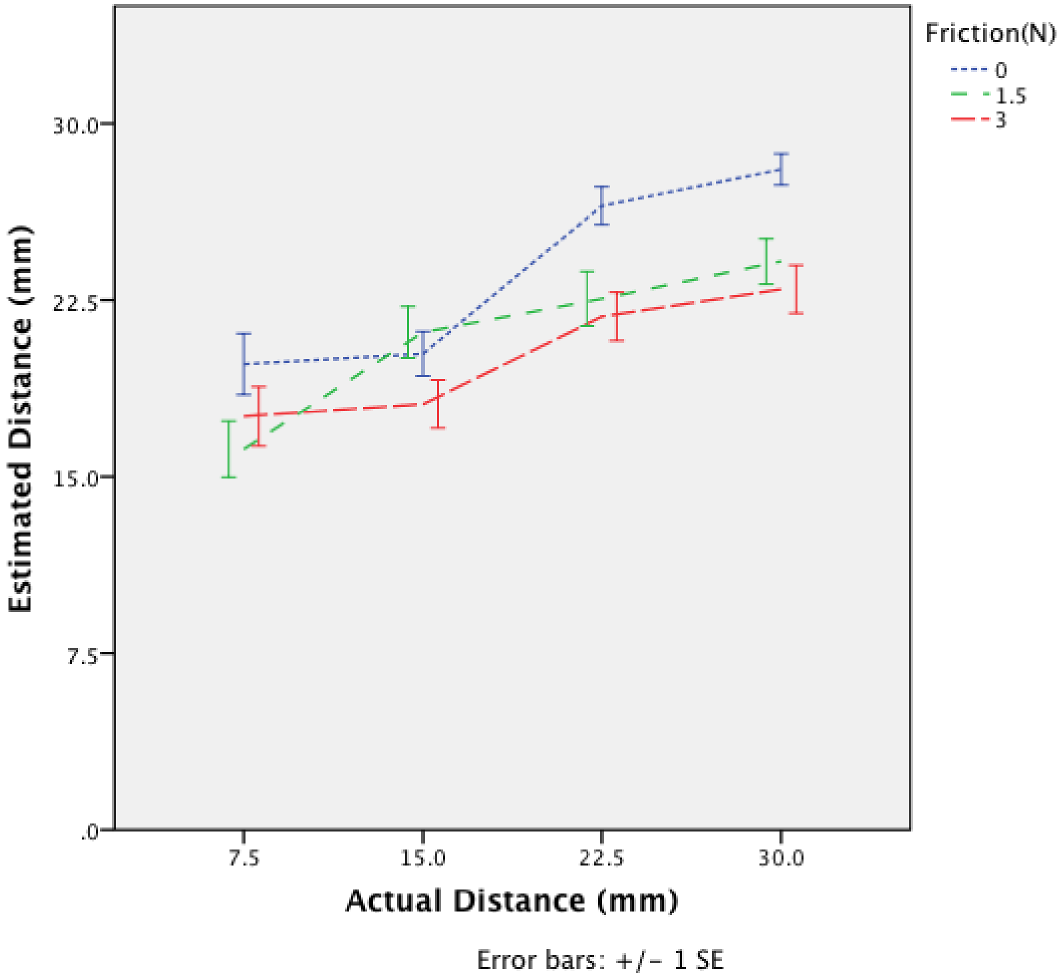

Figure 17. Average pretest break point estimates as a function of actual break point for all participants.

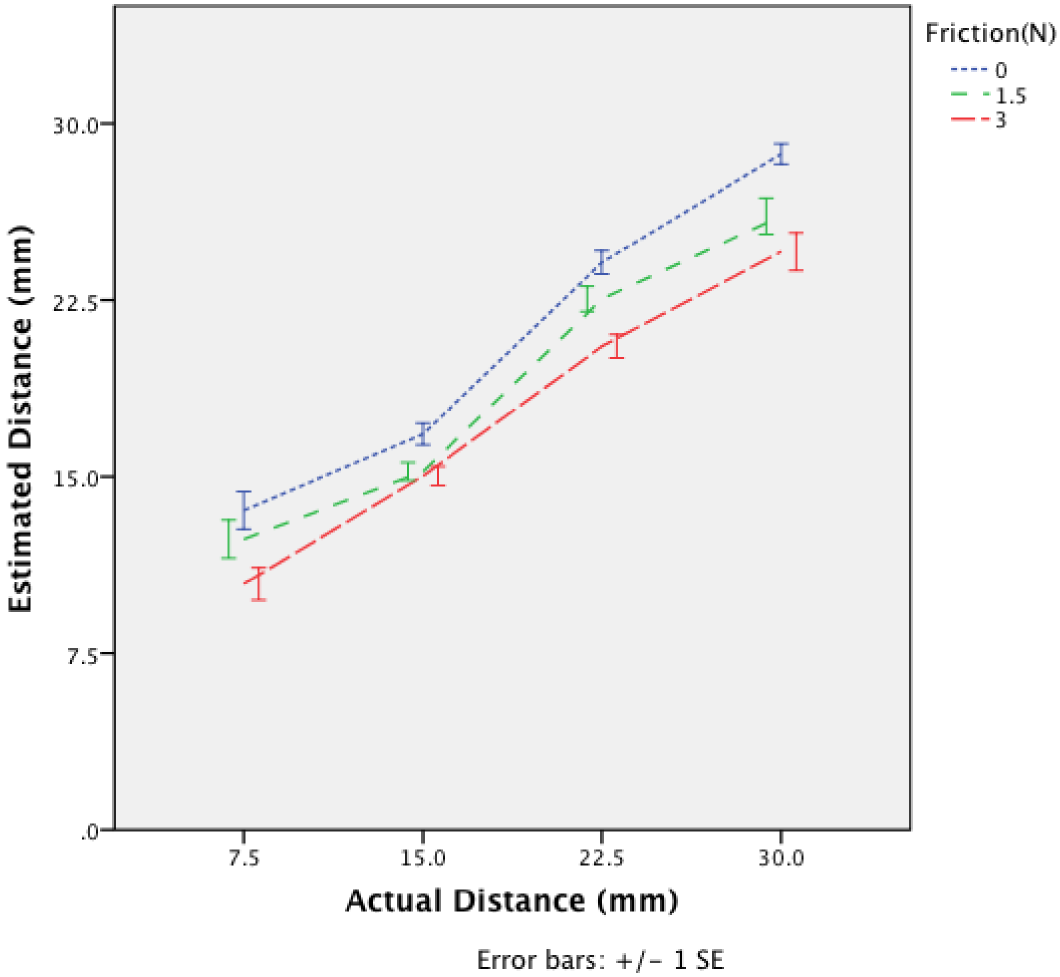

Figure 18. Average posttest break point estimates as a function of actual break point for all participants.

Simple regression models were used to determine the slopes and intercepts of the functions predicting indicated distance from actual break point distance for each participant. Then, they are used for the comparisons of the contributors to perceptual estimates of distance of actual target distance and actual force. Slopes, intercepts, and R^2

values for both metrics for each participant across phases are displayed in Tables 11a, 11b, 11c, and 11d.

Table 11a

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Pretest Phase for Each Participant

	Friction 1			Friction 2			Friction 3		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.360	.7	13.1	.434	.83	10.4	.435	.7	9.6
2	.748	.49	14.9	.155	-.31	20	.055	-.12	13.3
3	.011	.06	22.4	.653	.96	.8	.152	-.35	19.7
5	.005	.06	24.5	.988	.9	-.6	.118	.4	17.7
6	.036	.11	30.2	.179	.58	12.8	.563	.69	4.5
7	.043	.11	26.5	.230	.26	25	.281	-.38	32.6
9	.017	-.1	31.9	.65	.59	5.5	.192	.26	9.5
10	.374	.35	19.2	.119	-.3	26.5	.463	.54	8.7
11	.820	1	-.3	.860	.67	2.8	.015	-.07	30.1
12	.877	.68	4.3	.572	.38	9.7	.457	.54	6.2
13	.921	1	.4	.000	-.03	14.4	.303	.69	6.7
14	.950	.83	.2	.734	.73	2	.492	.41	3.3
15	.831	.67	12.2	.959	.86	4.1	.516	.61	8.9
17	.202	.29	11.7	.001	-.01	20.9	.273	.28	6.7
18	.234	-.2	34.8	.073	.15	25	.221	-.23	31.9
19	.114	-.26	18.2	.009	.03	10	.033	-.08	11.6
20	.485	.37	21.5	.046	-.13	27.8	.517	.24	24.8
21	.004	-.02	30.8	.001	.02	30.7	.057	.15	25.1
22	.027	-.08	32.7	.292	-.31	37.6	.264	-.41	36
23	.915	.87	7.7	.852	.72	11.8	.316	.52	10.5
25	.904	.86	2.8	.062	.26	6.9	.963	.77	4.8
26	.741	1.1	.2	.976	.99	-.9	.047	.25	22.2
27	.745	.63	5.3	.003	.03	32.4	.934	.86	1.4
Avg	**.451**	**.41**	**15.9**	**.385**	**.34**	**14.6**	**.333**	**.27**	**15**

Table 11b

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Feedback Phase for Each Participant

	Friction 1			Friction 2		
Participant	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**
1	.814	1.1	2.4	.852	.72	4.3
2	.992	.93	.8	.008	.12	15.3
3	.209	.47	10.3	.631	.91	.5
5	.805	.81	3.3	.898	.88	2.1
6	.673	.66	7.6	.813	.83	1.8
7	.650	1	2.2	.964	.94	1
9	.774	1.2	-1.3	.206	.46	7.4
10	.644	.69	3.6	.107	.44	6.8
11	.062	.31	16.6	.566	1	4.1
12	.246	.49	10	.340	.65	7
13	.999	1	-.3	.608	.76	2.2
14	.132	.37	15.6	.124	.2	10.9
15	.917	.87	1.8	.996	1	-.2
17	.867	.86	3.9	.066	.23	14.3
18	.634	.98	2.7	.022	.14	14.3
19	.967	.91	.5	.773	.9	.5
20	.158	.4	14.4	.523	.85	1.3
21	.361	.59	9.1	.964	1.13	-2.2
22	.106	.38	11.7	.421	.49	6.8
23	.797	.79	5	.780	.84	3.9
25	.998	.98	-.1	.270	.59	7.2
26	.980	1.08	-.8	.976	.97	.1
27	.067	-.18	31.8	.002	-.06	26.7
Avg	**.602**	**.73**	**6.6**	**.518**	**.65**	**5.9**

Table 11c

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the Posttest Phase for Each Participant

	Friction 1			Friction 2			Friction 3		
Participant	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**
1	.966	.9	3.9	.396	.71	3.2	.982	.97	.8
2	.994	.97	.3	.981	.93	.2	.990	.95	.7
3	.853	.96	5.4	.698	.75	8	.845	.73	6.7
5	.980	.97	-.1	.982	.31	.9	.993	.95	-.8
6	.095	.21	22.2	.427	.54	11	.768	.74	4
7	.817	.81	7.8	.568	.53	10.4	.919	.83	4.9
9	.867	.89	5.8	.916	.93	4.5	.747	.98	-1.5
10	.222	.39	11.5	.035	.16	10.7	.021	.1	11.9
11	.874	.8	6.2	.399	.53	11.3	.334	.38	14.5
12	.988	.87	2.7	.614	.69	4.4	.340	.37	7.9
13	.997	.94	.5	.993	.92	.2	.991	.94	.87
14	.898	.77	5	.245	.3	16.4	.000	.01	20.4
15	.965	.89	3.5	.984	.88	2	.652	.74	1.8
17	.919	.74	5.2	.747	.44	15.1	.042	.14	15.8
18	.409	.49	10.1	.879	.85	3.2	.919	.87	2.7
19	.387	.32	15.4	.314	.41	7.9	.716	.65	6.4
20	.965	.93	1.2	.183	.28	16.6	.084	-.23	23.7
21	.383	.33	19.6	.797	.66	9.9	.030	.09	12.2
22	.649	.51	11.5	.393	.33	7.2	.945	.74	2.4
23	.974	.83	3.8	.982	1.1	-3.1	.467	.65	3.2
25	.985	.75	3.9	.992	.9	.4	.845	.93	-1
26	.993	.92	-.6	.985	.95	-.5	.994	.95	-.04
27	.120	.19	25.5	.079	.18	20.1	.980	.86	2
Avg	**.752**	**.71**	**7.4**	**.634**	**.6**	**7**	**.635**	**.62**	**6.1**

Table 11d

Average R^2, Slope, and Intercepts of Simple Regressions Predicting Break Point Estimates from Actual Break Point during the ToT Phase for Each Participant

	Friction 1			Friction 2			Friction 3		
Participant	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**	**R^2**	**Slope**	**Intercept**
1	.995	.97	-.3	.992	.95	.1	.991	.95	-.4
2	.996	.9	.5	.994	.95	-.3	.996	.94	-.1
3	.994	.94	-.6	.98	.86	.7	.995	.94	-.2
5	.993	.92	-.2	.995	.9	-.1	.927	.87	-.4
6	.861	.58	4	.732	.57	5	.442	.39	4
7	.996	.94	-.1	.997	.97	-.3	.986	.9	.5
9	.962	.92	-.5	.928	.85	.8	.973	.94	-.7
10	.997	1	-.7	.892	.74	2.2	.847	.81	1.7
11	.996	.9	-.9	.993	.89	-.1	.996	.94	-.4
12	.995	.93	-.7	.845	.83	-.2	.993	.9	-.2
13	.994	.96	-.3	.993	.92	-.2	.993	.91	.2
14	.988	.92	-.1	.985	.86	1	.796	.58	4.3
15	.997	.89	.3	.994	.91	-.1	.998	.94	-.03
17	.92	.8	2	.665	.68	2.2	.572	.52	3.9
18	.986	.88	.9	.985	.9	-.1	.902	.79	2.3
19	.997	.92	.3	.991	.87	.4	.988	.83	1.1
20	.992	.93	-.1	.989	.87	.9	.973	.9	.6
21	.990	1	-1.3	.749	1	-5.8	.494	.7	2
22	.926	.74	2.1	.390	.41	5.8	.764	.65	4
23	.994	.89	.8	.992	.88	.5	.996	.9	.3
25	.977	.87	.5	.982	.87	1.4	.986	.9	.8
26	.995	.97	-.5	.997	.96	-.4	.999	.95	-.1
27	.991	.91	.1	.992	.86	.3	.996	.9	-.4
Avg	**.980**	**.90**	**.2**	**.915**	**.85**	**.6**	**.896**	**.83**	**1**

Comparing Pretest and Posttest Phases

Examination of Tables 11a-d reveals that across friction levels, the R^2 values did differ across phases. A 3x2 repeated measures ANOVA using the R^2 values from both phases confirmed that the R^2 values during pretest performance (M = .39, SE = .05) were significantly lower than during posttest performance (M = .674, SE = .052) $F(1, 22) = 21.465$, $p < .05$. There was, however, no significant effect in the difference in R^2 values of break point estimates for different friction levels $F(2, 44) = 1.529$, $p = .228$, or significant phase by friction interaction, $F(2, 44) = .151$, $p = .86$.

Slope values also differed across phases. A 3x2 repeated measures ANOVA using slope values from both phases revealed significant differences in break point estimates between the pretest (M = .343, SE = .065) and posttest (M = .652, SE = .049), $F(1, 22) = 21.001$, $p < .05$. There was, however, no effect of friction on break point estimates across participants $F(2, 44) = 1.627$, $p = .208$, or significant phase by friction interaction, $F(2, 44) = .198$, $p = .821$.

Similar to findings from R^2 and slope values, intercept values observed in simple regressions of individual participant performance also varied across phase. A 3x2 repeated measures ANOVA using intercept values from both phases in the control condition confirmed significant differences between pretest (M = 15.2, SE = 1.838) and posttest (M = 6.809, SE = 1.121), $F(1, 22) = 4.228$, $p = .051$. There was no effect across the different friction levels $F(2, 44) = .225$, $p = .799$, and no significant phase by friction interaction, $F(2, 44) = .135$, $p = .874$.

In short, the results showed an improvement in break point estimates in the posttest compared to the pretest, with R^2 and slope values closer to 1 and intercept values closer to 0, indicating a calibration effect that is characterized by an improved scaling of the estimates to the actual target break point distances. Next, multilevel modeling techniques were used to determine if phase and friction produced main effects while accounting for variance between and within participants.

Multilevel Modeling

Models similar to those employed in Experiment 1were used to analyze performance for the 23 participants in the experiment (N = 1622 trials). It was important to first use an intercepts-only model without predictors to provide a baseline (or null) model for the individual-level dependent variable, estimated distance, and to determine if MLM was appropriate. Results from the intercept-only model indicate an intraclass correlation (ICC) of .097, meaning that 9.7% of the total variance of break point estimates, resides between participants, and 90.3% resides within participants, which supports the mixed model approach. It is recommended that MLM analyses be used if ICC values exceed 0.05 (Heck et al., 2010).

Predictor variables were centered around the grand mean to allow for comparison of parameter estimates across models with both level-1 and level-2 predictors and to reduce possible effects of collinearity. Predictors were entered into the model hierarchically to determine their unique contribution to the model (see Table 12).

Comparing Pretest and Posttest. Predictors were added to the model as fixed effects and random effects one at a time. As with the previous push gesture experiment, all predictors produced significant fixed effects, and two produced significant random effects (actual distance and friction). As seen in Table 12, actual break point distance, actual break point force, phase, and friction all resulted in significant fixed effects, with actual distance resulting in the greatest R^2 effect size of 26.7% reduction in error variance, followed by friction, 3.9%, phase, 3%, and actual force, 0.6%. As seen in Figures 19 and 20 and Tables 11a & 11c, break point estimates for all friction levels became more accurate in the posttest, with slopes becoming closer to 1 and intercepts becoming closer to 0. Results were very similar to those in the push gesture experiment, both exhibiting the same fixed and random effects, with similar effect sizes. However, although performance significantly improved after training in the current experiment, phase reduced the error variance by only 3%, rather than 24.9% as with the push gesture experiment, which may be largely due to better pretest performance in the current experiment. It also appears that participants did not tend to overestimate break point estimates for materials with low force values (Materials 1 & 3) and no friction, as they did in the push gesture experiment.

Table 12

Estimates of Fixed Effects and Standard Error (SE) in the Experimental Condition

Effect	Model 1 Estimate (SE)	Model 2 Estimate (SE)	Model 3 Estimate (SE)	Model 4 Estimate (SE)	Model 5 Estimate (SE)
Intercept	20.399 (.592)	20.401 (.592)	20.403 (.593)	19.19 (.615)	19.181 (.614)
Actual Distance		.499 (.047)*	.533 (.048)*	.534 (.048)*	.536 (.048)*
Actual Force			-.635 (.188)*	-.639 (.184)*	-.644 (.176)*
Phase				2.42 (.33)*	2.429 (.315)*
Friction					-1.089 (.277)*
Change in Model R^2	--	.267	.006	.030	.039

*$p < .05$

Calculations for Changes in Model R^2

- Model 2 (unique effect of actual distance)
    - Model 1 residual – model 2 residual / model 1 residual
    - (66.478 – 48.72) / 66.478 = .267
- Model 3 (unique effect of actual force)
    - Model 2 residual – model 3 residual / model 2 residual
    - (48.72 – 48.42) / 48.72 = .006
- Model 4 (unique effect of phase)
    - Model 3 intercept – model 4 intercept / model 3 intercept
    - (48.42 – 46.985) / 48.42 = .030
- Model 5 (unique effect of friction)
    - Model 4 intercept – model 5 intercept / model 4 intercept
    - (46.985 – 45.157) / 46.985 = .039

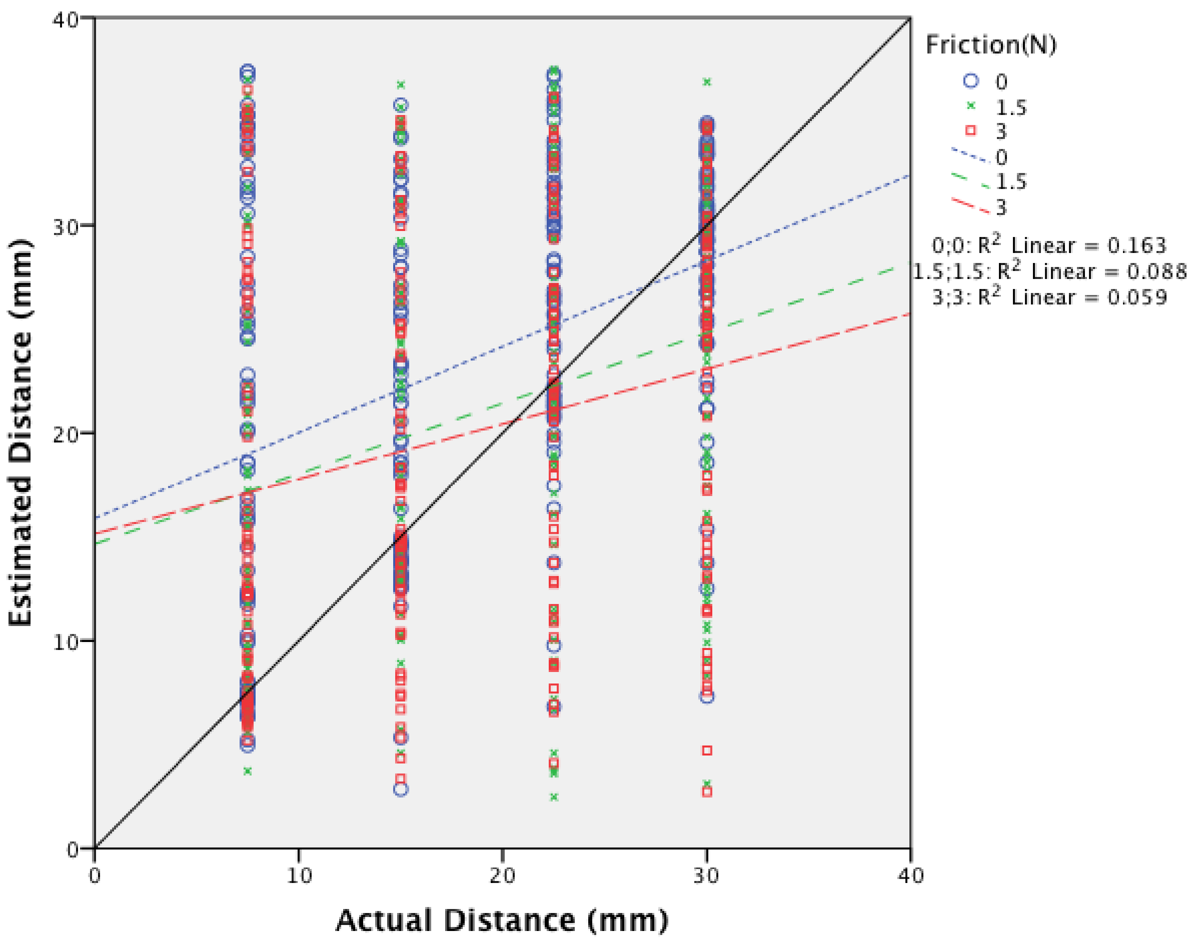

Figure 19. Pretest break point estimates as a function of actual break point for all participants.

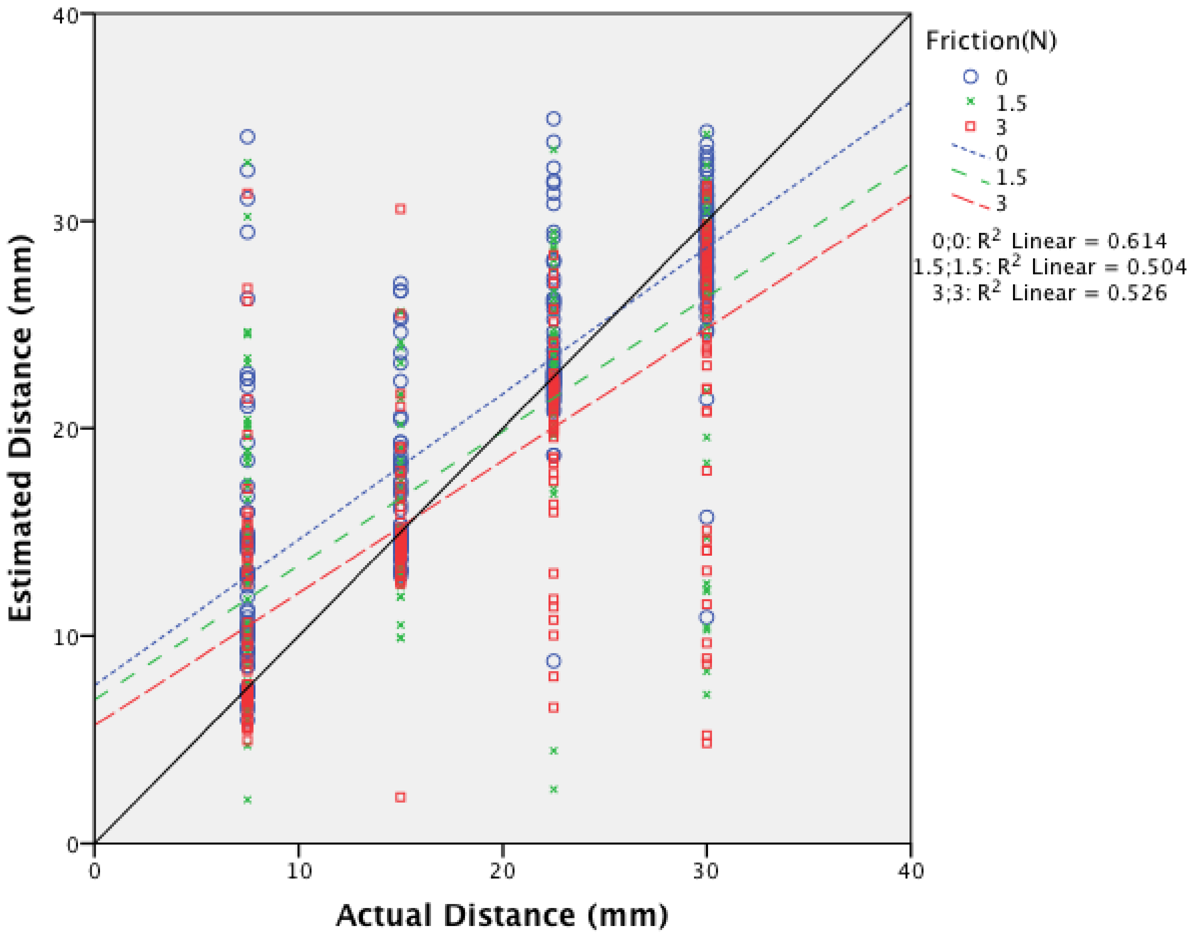

Figure 20. Posttest break point estimates as a function of actual break point for all participants.

Random effects. The intercept variance for those in the experimental condition was estimated as 7.51, $p < .05$, so the estimate of the standard deviation is 2.74. This suggests that there are unmeasured predictor variables for each participant that raise or lower their performance. Individual participants will have intercepts that are within 2.74 mm higher or lower than the group average about 68% of the time, and within 5.48 mm higher or lower 95% of the time.

Significant random effects of slope also occurred for predictors Actual Distance and Friction, p's < .05. This suggests that the slope of actual distance predicting estimated distance and friction predicting estimated distance varies for each participant. Individual participant's estimates predicted by actual distance will have slopes that vary within $\pm$0.2 mm of the group average 68% of the time, and within $\pm$0.41 mm of the group average 95% of the time. Individual participant's estimates predicted by friction will also have slopes that vary within $\pm$1.17 mm of the group average 68% of the time, and within $\pm$2.35 mm of the group average 95% of the time. This simply suggests that some participants produced more accurate break point estimates than others before training, and some participants' estimates were more affected by the presence of friction than others.

Transfer of Training Phase

Number of breaks compared across friction level and material are displayed in Table 13. Similar to Long et al. (2014) and Experiment 1, the majority of breaks occurred when materials required the lowest reactionary force before breaking (Materials 1 and 3). However, breaks do not appear to decrease as friction increases as they did in Experiment 1.

Table 13

Break Frequency Occurrence in the ToT Phase Across Material and Friction Level

Material	No Friction		Low Friction		High Friction		Total	
1	30/99	30.3%	21/91	23.1%	32/96	33.3%	**83/286**	**29%**
2	7/82	8.5%	2/74	2.7%	3/76	3.9%	**12/232**	**5.2%**
3	21/95	22.1%	10/82	12.2%	12/85	14.1%	**43/262**	**16.4%**
4	1/73	1.4%	0/75	0%	0/74	0%	**1/222**	**0.5%**
Total	**59/349**	**16.9%**	**33/322**	**10.2%**	**47/331**	**14.2%**	**139/1002**	**13.9%**

CHAPTER FOUR

GENERAL DISCUSSION

The current experiments demonstrated the ability of novices to detect soft tissue break points in the presence of friction, particularly in the context of a simulated MIS task. Two experiments were conducted to investigate whether participants were sensitive to DTB through applied force on a MIS tissue simulator. In the first experiment, participants probed four simulated soft tissues at three levels of friction (no friction, low friction, and high friction), where training was found to improve sensitivity to DTB through attunement and calibration. In the second experiment, participants' sensitivity to DTB was observed in a pulling task, another motion common during MIS procedures.

Hypothesis 1

It was hypothesized that participants are sensitive to DTB, which was supported with simple regressions of pretest performance for materials without friction simulated (Tables 4a, 5a, and 11a). Perfect performance would be represented as having R^2 and slope values of 1, and intercepts of 0. Simple regressions predicting break point estimates from actual tissue break point produced positive R^2 values of .373 and .289 for the experimental and control conditions in Experiment 1, respectively, and .451 in Experiment 2. Slope values were also positive values of .34 and .33 for the two groups in Experiment 1 and .41 in Experiment 2. Intercept values were 21.4 and 20.4 for the two groups in Experiment 1 and 15.9 in Experiment 2. These values indicate that participants could complete the task, although slopes of 21.4, 20.4, and 15.9 indicate overestimation of break points, especially for tissues that broke early.

Hypothesis 2

It was also hypothesized that novice participants are able to detect DTB with varying levels of friction present, which was supported with simple regressions of performance data in the pretest (Tables 4a, 5a, and 11a). Participants were able to complete the task in the pretest, with no difference in performance between experimental and control conditions. Multilevel modeling techniques revealed that the main contributor to break point estimates was the actual break point distance location, which participants must detect by utilizing the *change* in haptic force as distance into the tissue was manipulated. Even as lower-order parameters, actual break point distance and force, varied across materials, participants were successfully able to detect break points, indicating sensitivity to DTB. Because friction components do not affect the change in reactionary force as displacement into the tissue increases, it was hypothesized that participants would successfully be able to attune to DTB in the presence of friction.

Although there was an effect of friction on break point estimates, this appears to be due primarily to two trends. First, when 3N of friction, the highest level observed by a trocar in actual laparoscopic surgery (van den Dobbelsteen, Schooleman, & Dankelman, 2007), was applied participants tended to underestimate tissue break point, particularly as actual break point distance increased. In other words, when reactionary force was high immediately upon probing, participants were hesitant to push as far into the simulated tissue as when reactionary force was lower. Second, participants tended to overestimate the break point of tissues when no friction was present, particularly when the actual break point reactionary force was low. This result suggests that the presence of trocar friction may have the positive effect of causing users to be more cautious, and thus accidently breaking tissues less. Future research should investigate the possibility that this trend is likely caused by these materials of low reactionary force falling below perceptual threshold. Without perceiving contact with the tissue, break point estimates fell toward the end of the tissue simulator, as participants searched for contact.

Hypothesis 3

Performance data in the posttest supports the third hypothesis, that sensitivity to DTB is a skill that can be improved with training. Similar to Long et al. (2014), participant break point estimates were significantly more accurate after attunement and calibration to DTB during a brief training phase. These performance improvements were observed across all four materials and three friction levels, even though training only provided feedback for three of the materials and two of the friction levels, indicating sensitivity to DTB rather than lower-order parameters such as actual break point force and distance. . In Experiment 1, average R^2 values of participant performance in the posttest increased 58% for materials with no friction, 85% for those with low friction, and 93% for those with high friction compared to pretest performance, indicating that break point estimates were more consistent and precise as they became more sensitive to the mechanical information specifying DTB. Slopes of the simple regressions also significantly improved in the posttest, approaching perfect performance of 1, and intercepts significantly improved, approaching perfect performance of 0. Multilevel modeling also revealed that posttest performance was significantly better for those in the experimental condition than those in the control condition, who did not receive visual feedback after each estimate in the feedback phase.

Similar to the pretest, there was an effect of friction on break point estimates after training, reducing the error variance by 8.6% in the posttest compared to 4.3% in the pretest. Although the effect size was greater in the posttest, this increase in effect size was due to the improved performance despite friction, with the exception of the first material. Materials 1 and 3 may have been below perceptual threshold when friction was not present, with 90% and 77% of estimates in the pretest, respectively, and 81% and 64% of estimates in the posttest, respectively, exceeding the actual break point. However, break point estimates become more accurate on Material 1 as friction was added (see Figure 10). Because performance was much more accurate and consistent in the posttest compared to the pretest, this effect of friction appears larger in the posttest. Future research should investigate the possibility that friction actually causes fragile materials with break points below perceptual threshold to become above threshold. Unlike past research which has shown that friction can cause perceptual thresholds to increase (Perreault & Cao, 2006), the current study suggests that friction does not appear to be a variable that surgeons must overcome, but is something that surgeons can learn to ignore with training while it may simultaneously increase sensitivity to DTB. Friction may assist in the perception of other variables, such as reactionary force or distance, required to attune to DTB. These differences may be due to the different methodologies (training vs. no training), equipment (haptic simulator vs. real silicone materials), or differences in the fragility of materials presented.

Similar to Pagano and Cabe (2003; Pagano & Donahue, 1999), participants were successfully able to attune to and differentiate between useful haptic information and non-specifying variables. Just as the human perceptual system had shown to accurately perceive the length of a rod by attuning to the invariant of inertia, ignoring effects of wielding in different media, novices in both Experiment 1 and 2 were successfully able to ignore trocar friction, attuning to the invariant of DTB. However, there are times when the additional muscular forces needed to overcome the added friction may have made it easier to attune to useful information in the haptic array, which allowed participants in the current study to make more accurate break point estimates.

Hypothesis 4

It was hypothesized that sensitivity to DTB would transfer to a task where the participants must stop before the break point is reached, which was supported by performance in the ToT phase of both experiments. Simple regressions predicting break point estimates from actual break point (Tables 4d and 5d) for trials in which the break point was not exceeded reveal that estimates were near perfect performance, with an average R^2 value of .945 across friction levels in the experimental condition and .885 in the control condition of Experiment 1. In Experiment 2, R^2 values were similarly high, with an average of .930 across friction levels. Slope values were near perfect, with average values of 0.87 across friction levels in the experimental condition and 0.8 in the control condition of Experiment 1, and 0.86 in Experiment 2. Average intercept values were 0.8 in the experimental condition and 1.2 in the control condition of Experiment 1, and 0.6 in Experiment 2.

Participants only broke 12.1% of the tissues in the experimental condition, with breaks decreasing with increased friction, and 11.8% of the tissues in the control condition. Although participant estimates in the control condition appeared to be less accurate than those in the experimental condition, they did not break more tissues, likely due to practice effects and possible rapid calibration to DTB once haptic feedback was received upon breaking materials. Those in Experiment 2 only broke 13.9% of the tissues when pulling tissues. Similar to Long et al. (2014), breaks were most likely to occur when materials required the lowest reactionary force before breaking.

Hypothesis 5

Finally, it was also hypothesized that DTB generalizes to other MIS motions or tasks, such as pulling, which was supported by findings in Experiment 2, which employed the same procedure and materials as Experiment 1 but required that participants pull the simulated tissue rather than push to identify break point. Similar to the first experiment, participant break point estimates were significantly more accurate across all four materials and three friction levels after attunement and calibration to DTB during a brief training phase that only provided feedback for three of the materials and two of the friction levels. Performance in Experiment 2 revealed the same main effects (actual distance, actual force, phase, and friction) as observed in Experiment 1, and the same random effects (actual distance and friction).

Simple regressions of individual participant performance reveal that in Experiment 2, as in Experiment 1, R^2 values significantly improved 67% for materials without friction, 65% for materials with low friction, and 91% for materials with high friction after training, indicating that estimations became more precise and consistent. Slope and intercept values also became more accurate, approaching perfect performance of 1 and 0, respectively. However, unlike Experiment 1, Materials 1 and 3 did not appear to fall below perceptual threshold when friction was not present. Although these may still be difficult materials to detect break point because of the fragility, it's possible that the muscular forces needed to move the tool, hand and arm against gravity during the pulling motion, rather than with gravity as in the pushing motion, may have helped participants perceive the low force values. Thus in Experiment 2, gravity may have played the facilitating role served by friction in Experiment 1.

Conclusions

The current study was one of the first to examine how trocar friction affects soft tissue break point estimates within the context of a simulated MIS task. With a brief 10-minute training using our Core Haptic Skills Training Simulator, 18 to 20-year-old undergraduate psychology students' estimates of tissue break points significantly improved, even in the presence of friction. However, future research should continue to investigate certain shortcomings of the current experiments. For example, the current study only examined simulated tissues and simulated trocar friction. Future research should investigate if the observed improved performances transfer to real biological tissues and real trocars. Although the current simulated materials follow the exponential stress-strain pattern as exhibited in actual soft tissues (Brouwer et al., 2001; Fung, 1993; Rosen, et al., 2008; Yamada, 1970), it's important to determine if the training generalizes to actual surgical procedures and other stick and slip effects of the rubber trocar. If so, surgical training programs should employ the current haptic training to reduce the number of accidental breakage of healthy tissues during surgery. Future work should also research other possible types of feedback during training, such as haptic feedback alone, or a combination of visual and haptic feedback to maximize effects of attunement and calibration. Additionally, research should further investigate perceptual threshold for pushing motions and pulling motions and the possibility that the addition of friction can cause these fragile tissues to become perceptible.

One other shortcoming of the current experiments is that all participants were novice psychology students without any other surgical training. Past research, however, indicates that while experienced surgeons have an increased ability to detect DTB, their overall performance is very similar to that of the participant population employed in the present study (Long et al., 2014). Future work should confirm if the current findings generalize to actual surgeons, or if the improved performance resulting from the current methods only apply to those with no previous experience. However, it was also found that although surgeons demonstrated better performance than novices overall, some surgeons may be better at detecting DTB than others. Additionally, other research has demonstrated that receiving haptic feedback in a virtual training environment may be especially critical during early training phases for psychomotor skill acquisition (Ström et al., 2006).

Surprisingly, break point estimates in the current study became more accurate when friction was present than when it was absent. Previous research on friction and soft tissue break points in MIS has primarily assumed that friction is a hindrance, which surgeons must learn to overcome, and which engineers must work to reduce (Perreault & Cao, 2006; van den Dobbelsteen, Schooleman, & Dankelman, 2007). However, with other variables controlled, such as laparoscopic tool angle and visual feedback, it's possible that surgeons may be easily trained to attune to mechanical properties specifying DTB, using friction to assist them when reactionary force values of fragile tissues fall below perceptual threshold. Perhaps researchers should seek to identify an optimal level of friction, as too much friction may cause underestimation of break points, and too little may prevent fragile tissues from being haptically perceived. Minimizing preventable damages and injuries during MIS is achievable goal, one which can be improved by further research of mechanical information specifying DTB and by employing effective training MIS haptic training programs.

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APPENDICES

Appendix A

Demographics Questionnaire

ID	
Date	

Age:
Sex: (circle one) Male Female

1. Do you currently have any problems with your hands, arms, or neck?
Yes No

If yes, please describe:

2. Have you ever required surgery on your hands or arms (including fingers and wrists)?
Yes No

If yes, please describe (including which hand or both):

3. Do you currently have any vision problems aside from corrected vision?
Yes No

If yes, please describe:

4. Do you have any experience with videogames?
Yes No

If yes, estimated past usage or current hours per week:
If yes, list/describe your 3 most commonly played games and their respective consoles.

5. Does this include first-person perspective games (e.g. first-person shooter)?
Yes No

If yes, estimated past usage or current hours per week:
Please describe:

Appendix B

Effects of Friction

Table 14

T-values for Multiple Regression Analyses Predicting Break Point Estimates from Actual Break Point Distance, Actual Break Point Force, and Friction Level

	Pretest			Posttest		
Participant	**Actual Distance**	**Actual Force**	**Friction**	**Actual Distance**	**Actual Force**	**Friction**
1	1.99	-4.29**	-1.2	1.53	0.28	-5.35**
2	0.68	-1.82	-3.44**	6.99**	-2.26*	-5.08**
3	2.83**	-4.87**	1.13	4.86**	-2.9**	-7.9**
4	-1.49	0.71	-1.73	4.28**	-2.05	1.84
5	1.59	-2.23*	0.94	7.27**	-2.53*	-4.13**
6	3.15**	-3.56**	-6.61**	8.78**	-2.19*	-2.37*
7	1.33	-2.75*	-0.6	4.79**	1.02	-0.56
8	12.07**	-1.16	-1.94	5.85**	-1.73	-3.83**
9	6.38**	-1.77	-1.89	6.09**	-1.31	-1.92
10	-2.05*	-2.74*	2.19*	13.52**	0.82	-0.77
11	1.78	-0.81	0.003	7.13**	-0.03	-2.16*
12	1.83	-2.07*	0.38	5.04**	-1.13	-1.74
13	4.01**	-2.51*	-3.82**	7.05**	-1.66	-3.62**
14	44.86**	-3.17**	-0.74	74.68**	-6.56**	-6.51**
15	10.51**	-0.74	-4.24**	39.55**	-2.71*	-3.83**
16	0.57	-2.97**	-2.74*	4.68**	-1.67	-3.24**
17	2.56*	-2.85**	-2.34*	25.48**	-2.8**	-4.14**
18	3.71**	-0.74	-1.78	8.15**	-1.26	-0.75
19	3.63**	-0.97	-1.39	7.18**	-1.46	-2.22*
20	39.29**	-2.1*	3.92**	91.89**	-4.49**	-4.21**
21	10.21**	-1.57	1.42	13.25**	-0.38	-3.46**
22	7.21**	0.02	-0.36	58.15**	-1.87	-2.53*
24	-0.9	0.33	0.2	8.93**	-2.39*	-1.79
25	1.98	-3.66**	-3.13**	8.53**	-2.32*	-1.92
31	12.67**	-3.01**	-1.05	35.83**	-1.94	-1.23

*$p < .05$, **$p < .01$