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Effectiveness of a dynamic breast examination training model to improve clinical breast examination (CBE) skills

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Abstract

Despite the potential utility of clinical breast examination (CBE), doctors' palpation skills are often inadequate and difficult to train. CBE sensitivity ranges from 39–59%, in part because current training does not effectively teach tactile skills. To address CBE training limitations, we developed a breast examination training model with 15 dynamically controlled lumps, set to desired hardness within underlying rib and muscle structures, in a silicone breast. In an experiment of 48 medical students, training with the dynamic model increased lump detection by 1.35 lumps compared to 0.60 lumps for a traditional breast model ($P = 0.008$), reduced false positives by -0.70 lumps compared to $+0.42$ lumps ($P = 0.0277$), and demonstrated skill transfer with a 1.17 lump detection improvement on the traditional device compared to only a 0.17 lump detection improvement by traditional device trainees on the dynamic device ($P < 0.001$). Findings demonstrate the advantage of the dynamic model over conventional models in training CBE tactile skills.

Keywords: Palpation; Breast cancer; Training; Simulation; Tactile; Haptic

1. Introduction

1.1. Background

Breast cancer kills 40,000 women yearly in the United States, with approximately 200,000 new cases diagnosed in 2001 [1]. Fortunately, the 5-year survival rate exceeds 98% for tumors under 2.0 cm. Therefore, research has focused on early detection as one possible means of saving lives. Current screening methods include mammography, self breast examination (SBE), and clinical breast examination (CBE).

Evidence supporting the clinical efficacy of CBE emerged from the Canadian National Breast Screening Study and found that when performed in addition to CBE, mammography did not significantly affect the frequency of cancer diagnosis, stage at diagnosis, detection of interval cancers, or breast cancer mortality [2]. The Japanese national CBE program demonstrated a 40% decrease in the age adjusted mortality rate in municipalities given intensified CBE screening compared to control municipalities [3].

Despite its potential effectiveness [2,3], CBE sensitivity is only 39–59% [4]. It appears that physicians' skills vary widely and many physicians possess only modest clinical skills [5]. Often these skills fall short of performing a maximally effective CBE. Many practicing physicians, when surveyed, acknowledge a need to increase their competence in CBE. One study reported that 43% of primary care resident, faculty and nurse practitioners lack confidence in their CBE skills [5]. Practitioners may underutilize CBE if they do not feel proficient in CBE performance.

Performing an accurate CBE involves using a through search pattern, adequate pressure, proper finger positioning, and discriminating a solid mass from surrounding nodularity [6]. Breast palpation is a practiced tactile skill that does not necessarily correlate with cognitive knowledge about breast cancer detection [7]. Training which emphasizes tactile skills is known to improve examination sensitivity [8]. Currently,

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CBE is taught with live patient volunteers, artificial breast models, and training videos. The artificial breast models are the only modality that can reliably improve the tactile ability to identify masses, since patient volunteers may not have breast masses and the characteristics of masses that are present cannot be controlled.

Artificial breast models are made of silicone embedded with foreign objects representing tumors. The models are effective in improving lump detection [8]. Training with silicone models is also known to increase detection of benign lumps in live patients, demonstrating transfer of skills between the models and the clinical examination [9]. Optimally trained examiners can detect lumps as small as 2–3 mm [10]. Retraining and reassessment improve skill retention over time. After training, mean lump detection by trained participants has been seen to improve from 44 to 69% [11,12]. Careful training and supervision of health professionals has been reviewed in papers and subsequently modeled in hospitals [2,13].

Despite advances in tactile training with silicone breast models, CBE training in practice falls short. Two inherent characteristics of static silicone breast models limit their utility. First, the models provide a limited range of difficulty; once the trainee has identified all the lumps in these models, little more can be learned by repeating the examination. Second, training with static breast models increases sensitivity at the cost of increasing false detections [7,8,11], leading to a high false positive rate.

To address these limitations, we developed and tested a novel dynamic breast examination training device that can present the learner with up to fifteen lumps of varying characteristics in changing configurations. We built the model to address two important training issues: (1) range of difficulty (by gradually increasing difficulty from a set of larger, harder lumps to smaller, softer lumps) and (2) high false positive rate (by providing tactile feedback through active lump inflation/deflation beneath the fingertips). This breast examination model was then tested against standard, static breast models to determine its ability to train for improved lump detection, lowered false detection reports, and improved skill transfer.

2. Methods

We conducted an experiment to test the effectiveness of the dynamic training device in improving the lump detection and lowering false detections of CBE. We hypothesized that training with the dynamic breast model would lead to (1) higher lump detection, without increasing false detections, compared to training with a static silicone breast model; and (2) greater skill transfer to other breast models.

2.1. Breast models

The dynamic training model (Fig. 1) is a prototype silicone breast model with 15 lumps that can be individually inflated, to known, controllable levels of hardness [14]. The breast model includes simulated rib and intercostal muscle structures. Lumps vary in size (0.3–1.5 cm), hardness (20–50 durometers), depth of placement (shallow, medium, and deep), and fixedness (fixed and mobile). The silicone matrix is opaque and has a hard silicone backing with embedded ribs and entry points of thin, polyethylene tubes leading to the lumps of the same material. Lump hardness is controlled by an external pressure system, which selectively inflates the polyethylene sacs. Lumps are undetectable when deflated. The silicone matrix is homogeneous with little nodularity.

The control breast models (Fig. 1) are round opaque breast models with square bases. These static models are composed of a silicone matrix with embedded semi-solid lumps. The lumps are made of silicone polymers in a cylindrical shape. We used breast models CPM-S and CPM-F from the Mammatech Corporation, which are widely used to teach and evaluate breast examination skills [15]. The CPM-F model is firmer, but otherwise the two models are identical, with lump size, hardness, position, and depth being fixed and equal in both Mammacare models. The models have low nodularity.

Engineering tests including stress/strain analysis of breast tissue and tumor hardness were taken to ensure that the firmness of the dynamic and static models were similar. Additionally, a small, subjective test with fifteen

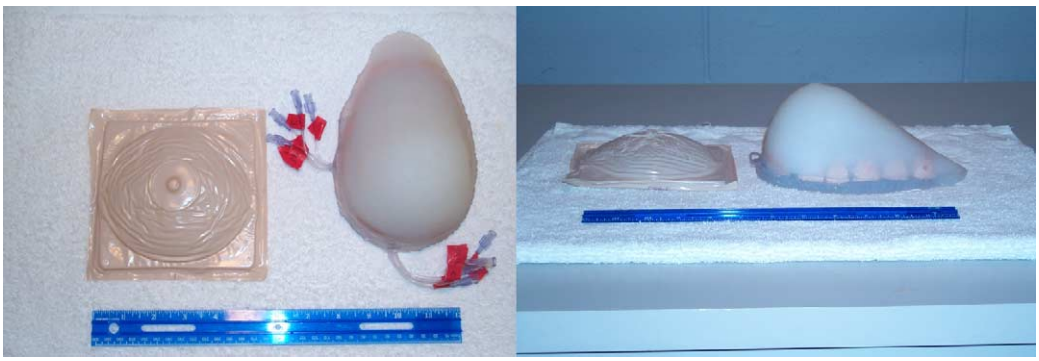

Fig. 1. Breast model comparison, static (left) and dynamic (right) with a 12 in. ruler.

physicians showed the dynamic simulator was similar to the Mammatech breast models in simulating real tissue [16].

2.2. Participants and study procedures

The 48 participants were first through third year medical students at the University of Iowa. They included 30 women and 18 men aged 22–40 with a mean age of 25. Participants were assigned to one of eight groups by order of response to the call for participants. We balanced the eight groups by gender and year in medical school, factors that reflect prior opportunities to practice breast examination techniques. Using eight groups enabled us to vary the order of tests 1 and 2 within each pre-test and post-test, to determine possible differences based on presentation order. Training groups A and B were each assigned 15 women and 9 men (8 first year, 15 second year, and 1 third year) (Fig. 2). All participants signed informed consent documents for the study, which was approved by the University of Iowa Institutional Review Board.

The experiment included two pre-tests, a training session, a break, and three post-tests (Fig. 2). Pre-test correct, missed, and false positive detection scores were gathered on each of the two models, where participants were allotted 2 min to examine each breast model. Participants reported locations of lumps and lump properties to the research assistant who recorded onto a scripted diagram. The 2 min examination interval is based on the time normally taken in a breast examination [8]. Because five lumps are fixed in the static model, five lumps with equivalent characteristics (size, hardness, and depth) were consistently inflated in the dynamic training model. Each 15 min training session included discussion and demonstration of recommended search pattern, finger pressure, part and number of fingers used, finger motion, nodularity effects, breast area coverage, and lump properties. The research assistant provided the training according to detailed, written instructions describing the above techniques.

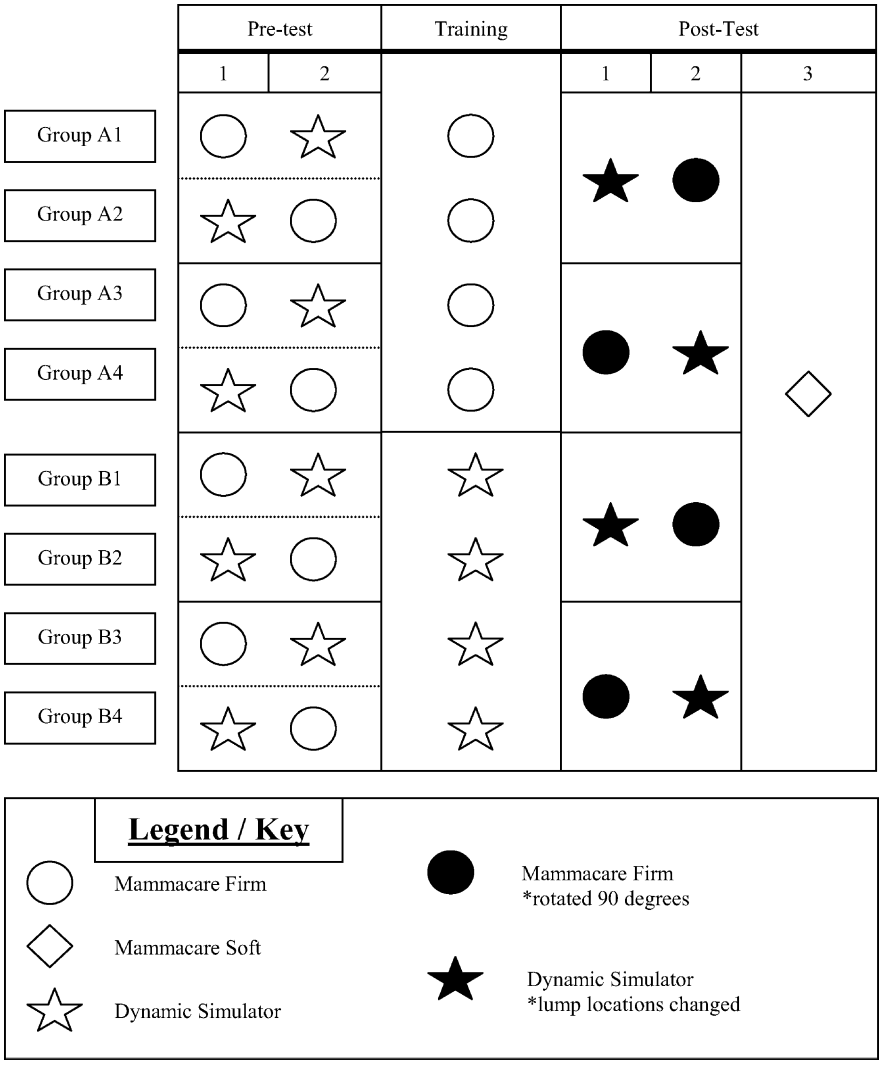

Fig. 2. Presentation order of the eight experimental groups.

With the dynamic model, lumps could be turned on and off, enabling trainees to palpate the same lump at varying hardness and distinguish it from background silicone material. Since this was not possible with the static model, participants in the control group alternately felt areas with and without lumps. After the 20 min rest, post-training scores were gathered on each of two models with order following from the trainee's particular group. Because all Mammacare breast models have identical lump configurations, we used the same firm static model (CPM-F) rotated 90°. The lump positions and properties were consistently changed in the dynamic training model with similar characteristics to the static model in terms of size, hardness, and depth [16]. To account for a possibility of bias in learning how the dynamic model operates, a third model (CPM-S) was introduced for the final post-test.

2.3. Statistical methods

Analysis of variance (ANOVA) techniques were utilized in comparing the data to determine differences among static and dynamic training groups. The independent variable (between-subjects dimension) was the training device (two levels: static, dynamic). The dependent variables (within-subjects dimension) were (1) the tested device (static, dynamic, third model) and (2) test condition (pretest and posttest), giving a repeated-measures design. Thus, we measured the correctly detected lumps to obtain pretest static and dynamic values and posttest static, dynamic, and third model values. We also measured false detections under each condition.

We performed three main analyses: lumps detected, false detections, and transfer of training for lumps detected. We intended to look at the differences based on type of training (static or dynamic).

3. Results

All 48 participants completed testing. Because presentation order in the first and second tests of pre-tests and post-tests did not significantly affect the results (composite lump detection: pre-test ($F(5, 42) = 0.07$, $P = 0.80$), post-test ($F(5, 42) = 0.05$, $P = 0.83$); and composite false positives: pre-test ($F(5, 42) = 2.45$, $P = 0.13$), post-test ($F(5, 42) = 1.17$, $P = 0.29$)), the eight groups were collapsed to two groups of 24 participants according to the independent variable (type of training: static or dynamic).

3.1. Lump detection

Each participant has two lump detection measures: the pre-test to post-test difference in the number of lumps found for (1) the static model and (2) the dynamic model. Composite lump detection improvement was defined as the sum of the lump detection improvement on the static model and the lump detection improvement on the dynamic model. Composite lump detection improvement (Fig. 3) was greater after training with the dynamic training model (1.35 lumps, S.D. = 0.92) than after training with the static device (0.60 lumps, S.D. = 0.96) ($P = 0.008$). The participants who trained on the dynamic model showed a trend toward detecting more lumps on the third model introduced at the end of the experiment, but this result was not statistically significant (dynamic model: 3.04 of 5 lumps, S.D. = 1.12; static model: 2.54 lumps, S.D. = 0.88) ($P = 0.0927$).

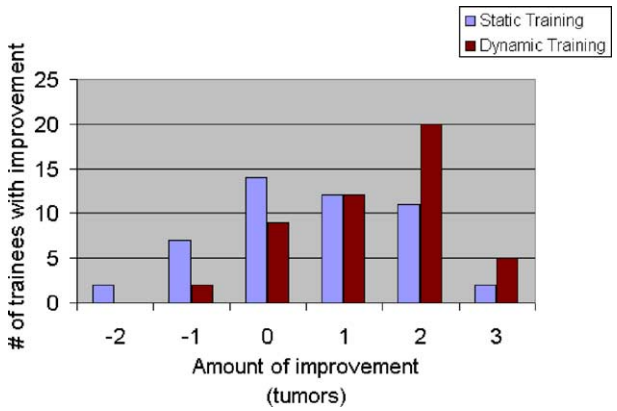

Fig. 3. Composite lump detection increase (static + dynamic) based upon training model.

3.2. False detections

A false positive detection is the incorrect claim that a tumor is present where it is absent. False positive detections significantly decreased between the pre-tests and the post-tests after dynamic training (−0.70 false lumps, S.D. = 0.97) (Fig. 4), but increased after static training (+0.42 false lumps, S.D. = 0.62), as measured by the number of false

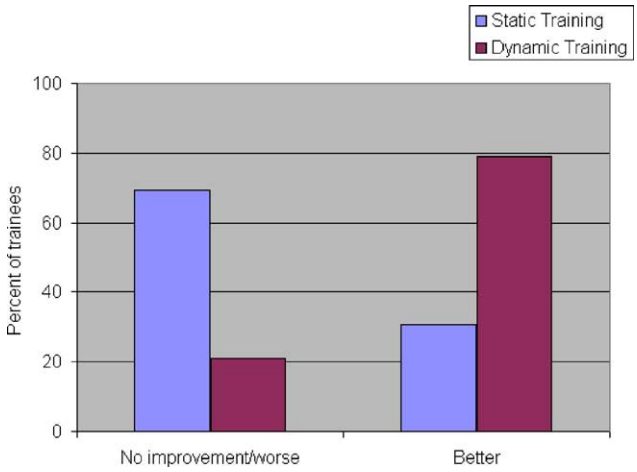

Fig. 4. Change in false detections based upon training model (includes 13 of 24 static trainees and 19 of 24 dynamic trainees who reported false positives on either pre-test or post-test and excludes those who never reported a false positive).

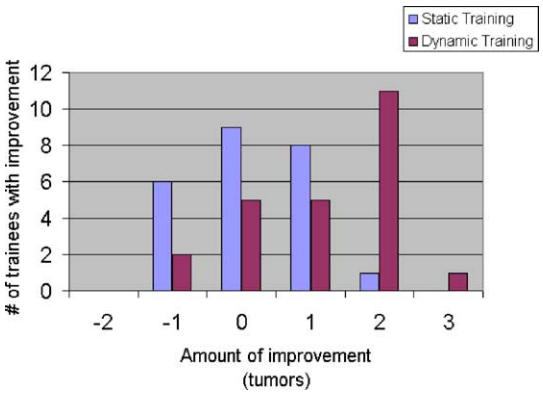

Fig. 5. Transfer of training lump detection improvement based upon training model (ability to locate lumps on the breast model that participants were not trained for).

positives reported after training minus the number of false positives before training ($P = 0.0277$). Third model false positive detections were also significantly lower after dynamic training than after static training; static training participants reported an average of 0.625 false positives (S.D. = 0.82) versus 0.125 reported by dynamic training participants (S.D. = 0.34), which is also statistically significant ($P = 0.0133$).

3.3. Transfer of training

Transfer of training refers to whether training with one model improves skill performance on the other model. Training on the dynamic model improved lump detection in the static device post-test, but training with the static device did not affect lump detection in the dynamic device post-test (Figs. 5 and 6).

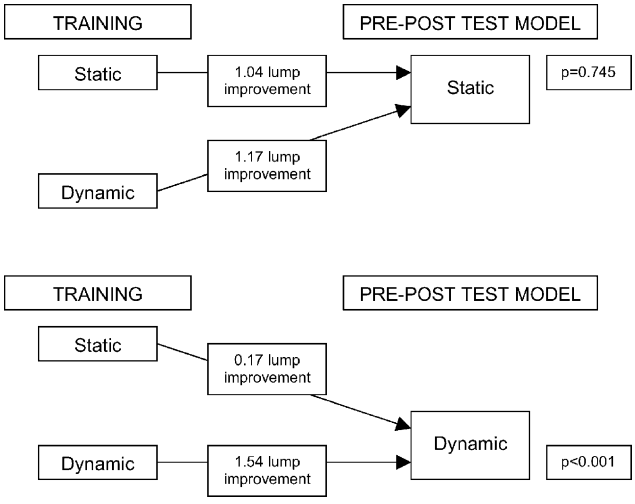

Fig. 6. Transfer of training lump detection improvement based upon training model. Top Diagram shows pretest to posttest improvement as tested by the static model. Bottom diagram presents pretest to posttest improvement as tested by the dynamic model.

4. Discussion

We found that training on the dynamic breast model leads to higher lump detection and greater skill transfer across breast models compared to training with a static breast model. This improvement occurs without increasing false-positive reports, a concern associated with static model training using currently available models. Compared to static model training, dynamic model training led to more lumps detected, fewer false positive reports (false detections), and superior post-test performance on both dynamic and static devices (transfer of training). Three important experimental results were statistically significant at $P < 0.05$. The findings demonstrate that dynamic training has the potential to improve CBE skills. We also obtained insights into necessary model improvements for training of CBE palpation skills.

Experimentally, the composite improvement after dynamic model training shows nearly a one lump advantage. This improvement is impressive after only one 15 min training session.

On the third model post-test, the trainees in the dynamic model group showed a trend toward detecting more tumors than trainees in the static model group. This trend is interesting because the third model was essentially identical to the static model used in the pre-test, training, and post-test. This similarity should have given a significant advantage to the static device training group, because lumps with identical properties were situated in exactly the same locations as the training model (although rotated by 90°), with only a slightly softer silicone.

Dynamic model training decreased false positives compared to static model training. In the clinic, false positive detections translate to patient anxiety and unnecessary tests. Previous studies have shown that static Mammacare models increase sensitivity at the cost of increasing the number of false detections, leading to a high false-positive rate [7,8,11]. We recognize that reducing false positives risks a loss of sensitivity, and our goal is to reduce false positives while retaining a high level of sensitivity, i.e. by teaching discrimination. We believe that teaching subtle differences in stages will improve discrimination and avoid possible confusion between benign nodularity and lumps.

The effect on transfer of training is the most promising aspect of the dynamic model. Transfer of training refers to whether training with one model improves skill performance on the other model. In training situations, transfer is ultimately the most important instructional outcome [17], because it ultimately refers to the extent of improved task performance as reflected in real-world task execution. Training CBE palpation skills requires adaptation to different tissue types, but the Mammacare models seem to develop specialized skills that do not generalize to the dynamic model. Dynamic model trainees performed better not only on the trained device, but also on the static device. This suggests that dynamic training may transfer better to real breast

tissue than the static models. The static device may develop a subset of skills, specific to itself, rather than general skills that apply to other breast models or to real breast tissue. While the dynamic model is not currently in commercial development, a cost comparison may be evaluated with a standardized patient at US$ 150, both CPM models at US$ 120, and the dynamic prototype at approximately US$ 200.

Future work includes refining the dynamic training model, measuring its educational efficacy, and exploring training transfer to clinical experience. We also intend to develop nodularity, which could change dynamically in addition to a configurable breast density. Our overall end goal is to confirm that skills learned with the dynamic model can transfer to tests with live patients.

5. Conclusions

The tactile sense is often forgotten or taken for granted, yet it can be trained to detect stimuli at spatial resolutions rivaling those of sight [18]. Our dynamic breast model has the potential to accurately determine the trainee's level of skill, allowing learners to reach and maintain predefined levels of proficiency. CBE is a useful tool for early detection because it is practical, inexpensive, and highly effective with proper training [2]. With objectively uniform training, CBE can potentially become very reliable, consistent, and effective. In view of the untapped potential of the trained tactile sense, the limitations of mammography, and the potential for CBE to improve early detection of breast cancer (of societal benefit especially to third world countries), improved, consistent training could have a significant impact on the efficacy of mass screening with CBE.

Acknowledgements

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