The relationship between tap pressure on pressure sensitive touchscreens and the users's emotional state

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ABSTRACT
The detection of emotion has been a subject of research for a long time and is key to affective computing; computers that assist humans or have an enhanced decision ability based on the user. One of the areas that recently has become available is pressure sensitive touchscreens. Touchscreens are a widely accepted and used technology where users deliberately interact with multiple times per day. This study tries to predict emotion from tap pressure by using a pressure sensitive touchscreen and an affective picture database. Unfortunately, while literature does suggest a correlation, this study finds none, $p > .05$. Additionally, a small study is performed to explore a relationship between tap pressure and tap duration, which does show significance, $p < .0005$ The discussion raises some weaknesses as to the cause and proposes several solutions for further investigation.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation: User-centered design

Author Keywords
Human centered multimedia; emotion; tap pressure; motor expression

Theodore: *Are you in love with anybody else?*
Samantha: *Why do you ask that?*
Theodore: *I do not know. Are you?*
Samantha: *I've been thinking about how to talk to you about this.*
Theodore: *How many others?*
Samantha: *641.*

Her (2013)

INTRODUCTION
Would it be possible to measure emotional state from tap pressure on touchscreens? The field where this study fits in is called affective computing. It concerns itself with computers that have the means to detect, respond, and express emotion.

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The goal of this study is more specific, it will be within the field of emotion detection of computers and explores the use of pressure sensitive touchscreens of smart devices as means for a less intrusive, more ubiquitous and less intrusive way of detecting emotion.

Reeves et al. [25] have shown that humans have the unconscious and unintentional response to computers to act in a natural and social way. It means that people are unware that they change their behaviour to communicate with computers as if they were a social peer. Emotion aware smart devices could provide users with a better experience, where better can be classified as an experience in line with how the user is feeling. Screens and information that present themselves in different ways, where the differences originate from current feelings of the user. Picard [22] states that computers that are emotion aware not only possess the ability to be of the users' assistance but also let that computer make decisions that are influenced by those emotions that are expressed by the user. This type of adaptation of user interfaces and information can tighten the social bond between user and smart devices making the devices feel more alive. Furthermore, the current state of technology, and in particular machine learning, is capable of using the emotion of users in product designs that dynamically change. However, Zimmerman et al. [34] are uncertain what emotional reactions are adequate of a system that is aware of the users' feelings. Having a smartphone as personal companion with oneself on a day-to-day basis could provide assistance in multiple ways. Lindstrom [19] showed that, using an MRI machine, the regions in the brain that are active when someone is in love are the same parts that are active when someone hears their smartphone ring. The statement was met with critique, mostly because Yarkoni et al. [33] showed that the insular cortex, the region that was active in Lindstrom's research, is active in a third of the studies that utilize MRI. It also shows that the region is active for several other emotion as well, amongst which digust. However, it still proves that people experience strong emotions when handling their smartphones. If users have these strong feelings towards their smartphone and also try to act in a natural, social way with them, why not try to make those small computers respond in a natural, social way as well?

Further reading of this section is divided into four parts; models of emotion, measuring of emotion, practical and applied applications, and research question and hypotheses. Models of emotion will help to grasp the different ways to approach and

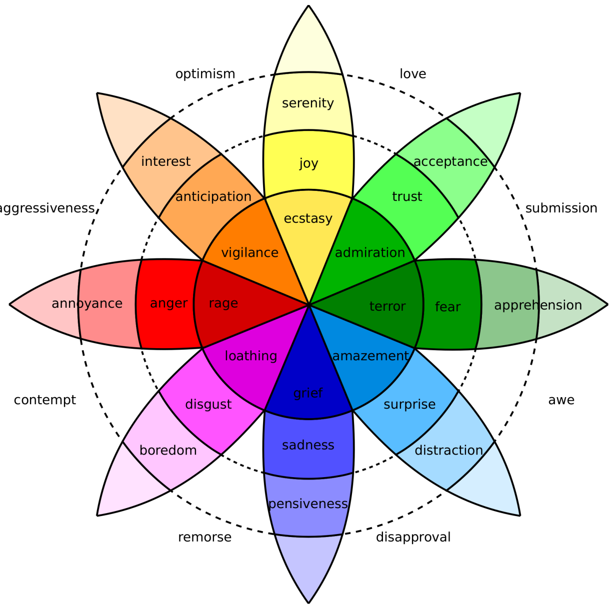

Figure 1: The discrete three dimensional model that R. Plutchik [23] introduced in 1980. It shows human emotions on a discrete scale, where the most intense emotion is displayed in the middle, and intensity drops when going outwards. It has been evaluated for use for this study, but the choice was made to use a continuous model as will be explained later.

classify emotions, whereas measuring of emotion will help understand how measuring is currently executed and how it can be improved. Subsequently, several applied applications are discussed in order to explore the existing landscape of emotion detection in practice. Finally, before moving on to the methods, a research question and a hypothesis are presented.

Models of emotion

There exist several different models of emotion that attempt to classify human emotion in varying ways. In 2000, Scherer [26] presents four models to represent emotion: (a) dimensional, (b) discrete emotion, (c) meaning, and (d) componential. Their focus lies respectively with subjective feeling, motor expression and adaptive behavior patterns, verbal descriptions of subjective feelings, and the link between emotion-antecedent evaluation and differentiated reaction patterns. The study tries to name often used elicitation mechanisms; however, it fails to find specific mechanisms for all but the componential model, which often uses an appraisal mechanism. Appraisal is one of the six components that Fontaine et al. [8] incorporate in their model of emotions. The complete model that they present consists of six components: (a) appraisals of events (b) psychophysiological changes, (c) motor expressions, (d) action tendencies, (e) subjective experiences, and (f) emotion regulation.

More recently, Shah et al. [27] state that there are in general two directions to represent emotion; discrete and continuous. The discrete model represents emotions that are measurable and physiologically distinct like angry, sad, happy, and others [5]. A more detailed discrete model is the one proposed by

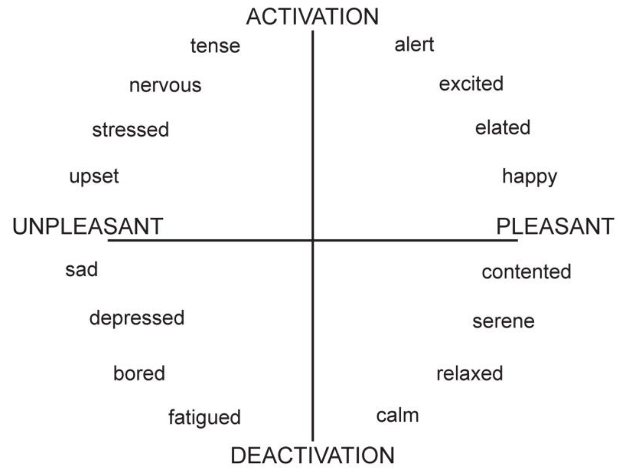

Figure 2: The two dimensional model as explained by Posner et al. [24]. Valence is expressed on the x-axis, arousal on the y-axis. Rather than classifying each emotion discretely, it can put emotion anywhere on the two axes

Plutchik [23]. The continuous model represents emotions on a two-dimensional scale, where one axis represents *valence* and the other *arousal* [24] (Figure 2). Mauss et al. [20] suggest that using a dimensional, continuous framework is a better option when capturing emotion, relative to discrete frameworks.

Physiological detection

The first domain uses physiological signals of the human body to measure and detect emotion. In a review by Wioleta[32], eight studies were collected that measure emotion using one or more physiological signals combined. These signals are (in no particular order): (a) EEG, (b) skin conductance, (c) blood volume pulse, (d) temperature, (e) heart rate, (f) blood pressure, (g) respiration, (h) EMG, and (i) ECG. Most of these physiological signals have the drawback that they need specialized sensors attached to the body, making unobtrusive measurements difficult. With the recent rise of smart wearables that include a heart rate monitor, heart rate is one of the signals that is more readily available to use in applications on smart devices.

Facial detection

Facial detection of emotion incorporates the measurement of facial muscle movement, voice or speech [30], and furthermore includes the eye as point of detection, i.e. movement, blinking, and pupil dilation [29]. While one can argue that these methods are also physiological, they are researched to such detail and extent that they can be classified separately. By connecting facial muscle movement to the visual display of emotions, Ekman et al. [6] conclude with a core set of six mutually exclusive emotions that could be recognized. Furthermore, De Silva et al. [28] found that several emotions are expressed by either visual or auditory cues, or both, meaning that some emotions can be recognized by visual cues alone, auditory cues alone, or need a combination of both to be detected accurately.

Posture/gestures emotion detection

Other means of detection emotions involve the tracking and interpretation of posture and gesture. Wallbott et al. [31] concluded in 1998 that there are, in some cases, distinctive patterns of movement and postural behavior that have a strong correlation to emotions. In other cases, they mention that in the absence of patterns there are still distinctive features from which emotion can be inferred. Coulson et al. [3] researched static body postures and the recognition of emotions from these body postures by participants. It showed that disgust is a tough emotion to recognize but anger and sadness had over 90% correct detection rates. Furthermore, they conclude that happiness and surprise were two emotions that were often confused.

Applied emotion and pressure detection

First, Hertenstein et al. [15] show that touch can communicate distinct emotions. Looking at the more practical and applied side of emotion detection, Gao et al. [10] used touchscreen devices, where the application of gestures on touchscreens is successfully linked to emotional states with the use of a game. The emotional states that were tested for are: excited, relaxed, frustrated and bored, and accuracy of detection reached at minimum 69%. However, the research of Gao et al. was limited to gestures and did not incorporate data from taps. Furthermore, Lv et al. [14] have created means to detect emotion from keyboard pressure using feature extraction. This indicates that the use of a keyboard on a touchscreen could also be used as means of detecting emotion, but one must keep in mind that a regular keyboard is not entirely comparable to a touchscreen keyboard. It lays flat on a desk and is often typed upon with more than one or two fingers, which means that the pressure exerted on the keyboard is likely not directly correlated with the pressure on a touchscreen keyboard. Moreover, Lee et al. [17] propose an unobtrusive way of detecting emotion by analyzing smartphone usage patterns (not unlike LiKamWa et al. [18]) and social network status updates. However, this required that the user would post status updates through independently developed social networking applications, that are not officially supported by the social networks themselves and which could possibly invade privacy. Grünerbl et al. [13] employ a smartphone and sensor fusion to detect 17 emotional states and state changes in bipolar disorder patients. Utilizing pattern recognition of phone call features, speech features, GPS data, and accelerometer data, 76% recognition accuracy is reached. This study did not use invasive body sensors but does use data of (amongst others) phone calls like unique numbers dialed, the average length of phone calls, and percentage of speaking in the whole conversation. This is privacy sensitive data that is analyzed for emotion detection. Essl et al. [7] have studied touch-width based force-like sensing using the Android API for musical instruments. It infers touch pressure based on the total surface area of a finger that touches the screen, and the approach by Essl et al. resulted in four distinct pressure levels using only built-in sensors of a smartphone. Goel et al. [11] developed GripSense, another way to continuously detect pressure rather than a one-time approximate detection as Essl et al. performed. By using the vibration motor and gyroscope in a smartphone, three distinct pressure levels could be detected with a 95.1% accuracy.

Research question and hypotheses

From the reviewed literature it can be concluded that measuring emotion often requires invasive sensors attached to the body to measure various physiological signals, invades privacy by constantly analyzing camera images or microphone signals, or requires the user to execute specific actions like playing a game or entering text. The practical applications show one thing in common: a touchscreen. The touchscreen is a technology many people interact with every day, where they deliberately choose to participate in those interactions and is independent of a use case if the user does not need to access a specific app or website. Using touchscreen presses as indicators for an emotional state could be an unintrusive way of detecting emotion without the need for constant monitoring through other sensors. With the introduction of pressure sensitive touchscreens in recent smart devices, an interesting new sensor is added to the plethora of sensors already available, which leads to the following research question:

Can pressure sensitive touchscreen devices be used to tell more about the emotional state of the user?

The presented research question prompts thorough investigation of the connection between the pressure that a tap exerts on a touchscreen and the emotional state of the user that performs the taps. It sets the scope of the study to motor expression analysis, one of the six components mentioned by Fontaine et al. [8]. The null hypothesis that springs from the research question is:

H_0: *Pressure of taps on touchscreens exhibit no correlation with emotional state.*

and the alternative hypothesis:

H_1: *Pressure of taps on touchscreens exhibit direct correlation with emotional state.*

Furthermore, the data that is collected during the experiment allows for a smaller study besides the main research question. It concerns the relationship of tap pressure and tap duration. Interest for this smaller study stems from the unavailability of pressure sensitive touchscreens. They have become more common, but only one major smartphone manufacturer utilizes them. If tap pressure and tap duration show a relationship, it indicates that any touchscreen can be used for predicting tap pressure without the need for pressure sensitive touchscreens. The next section will present how the study was conducted before it continues to present the results.

METHODS

In order to test for the correlation between taps on a touchscreen and emotion, there has to be a standardized way of eliciting different emotions and a measurement plan for tap pressure. Besides explaining the methods for the main study, this section also explains the methods of the beforementioned smaller, second study that will explore a relationship between tap pressure and tap duration. For this experiment, 51 Participants were selected using a convenience sampling process at an office. The participants varied in age, educational level, current line of work, and background.

Emotional elicitation

For the experiment, a standardized photographic test image set has been used that often has been used succesfully for measuring emotional response of viewers. This photo set measured emotional response a two-dimensional valence and arousal scale and is called the Geneva Affective Picture Database [4]. Utilizing the emotional responses elicited by this photo set as a baseline, touchscreen taps and their pressure can be compared to the emotional response. The photo set counts 730 pictures and is divided into six categories: Animal, Human, Neutral, Positive, Snakes, Spiders. From each of the categories, ten pictures were randomly selected, resulting in a set of 60 pictures used for the experiment. Each participant was presented with the same 60 pictures, but in random order in order to mitigate any side effects that might occur from presenting pictures in a particular order. Brown et al. [21] remark that 5-second exposure to pictures is often used for the IAPS (International Affective Picture System) [**?**] photos. The GAPED photo set has been created because of two issues with the IAPS; extensive use decreases the impact of the stimuli and the limited number of pictures for specific themes. Both these issues are not exposure time related, so the choice of exposure time of the photo to the participant is five seconds.

Pressure detection

Taps were detected on an Apple iPhone 6s device with a 3D touchscreen running iOS 10.3.1. The pressure of taps was registered on a floating point scale from 0.0 to 6.67 (Corresponding with 0 to ± 350 grams). For every tap, several pressure measurements were registered in chronological order. Furthermore, the duration of a tap (in nanoseconds) was recorded.

Data collection

In order to collect a larger data set, four taps per photo were required to advance to the next photo. These taps are directed with the use of gray colored buttons that are randomly shown on a four by four grid on the screen (Figure 3). The random pattern of the buttons ensures that the position of the tap on the screen does not matter for the pressure measurement once the tap pressures are averaged. It uses a gray color because it is perceived as neutral. The buttons are random for every photo, and for every participant. In other words, no participant received the same grid for the same photo.

All the data that was collected was anonymously and securely sent real-time to a Firebase [12] database. Firebase utilizes a JSON [16] tree structure that is described in Figure 4. The figure also provides are more detailed look into which data was collected and the experiment setup.

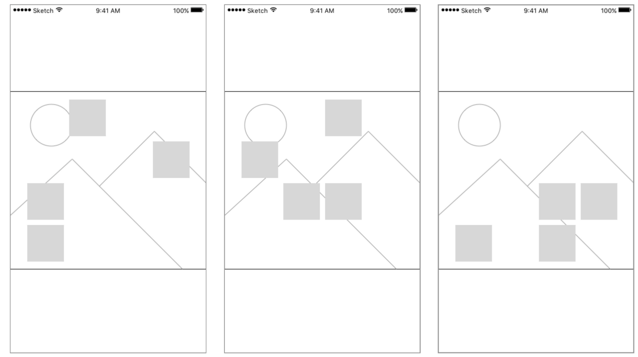

Figure 3: Three examples of the grid as presented over a picture shown on a smartphone. When a participant has pressed each of the gray squares (which disappear when pressed upon) the next picture is shown. After five seconds a new randomly generated grid is displayed on top of the picture. This process repeats 60 times.

Experiment setup

Firstly, participants were informed about what the experiment entailed and were presented with a consent form. Subsequently, the participants continued the experiment on the smart device with a test application. The entirety of the experiment was completed in a room that contained no screens, speakers or other distractions, otherwise known as the 'Zen room', and ensured the participants were focused on the experiment. The test application was structured as follows:

1. The participant is presented with a screen that asks if they received and signed a consent form and if not, that they should contact the supervisor immediately. There is also a *start* button to start the experiment.
2. If the participant pressed the *start* button, the first picture is shown.
3. After five seconds, four gray buttons are shown, overlaid on the picture in a random pattern (Figure 3).
4. When the participant pressed all the four buttons, the next picture is presented.
5. This process repeats until all 60 pictures were shown.
6. The participant is presented with a final screen that contains a thank you message and refers to the supervisor if there are questions.

When the experiment had concluded, participants were informed about the nature of the experiment (i.e. they were informed of the research question) and any questions they asked were answered.

Data analysis

The collected data was exported as JSON from Firebase and subsequently mutated using Python 2.7 [9] on macOS 10.12.4 [1] in order to create an *.csv* file that was readable by SPSS 24.0.0.0 [2]. Because of a suspicion that either maximum exerted pressure or average exerted pressure of a tap might be

Root

- Experiment 1
  - Photo 1
    - Tap 1
      - *Pressure measurement 1*
      - *Pressure measurement 2*
      - *…*
      - *Pressure measurement N*
      - *Duration of tap*
    - Tap 2
    - Tap 3
    - Tap 4
  - Photo 2
  - …
  - Photo 60
- Experiment 2
- …
- Experiment *N*

Figure 4: The database structure shows that for every experiment entry, there are 60 photo entries. Each photo entry contains four tap entries, that contain zero to *n* pressure measurements and a duration measurement.

of influence, these two variables were manually added using averaging. For maximum pressure, the maximum pressure value of each tap was extracted, and for each photo, this was averaged. Regarding average tap pressure, the average pressure of a tap was calculated and subsequently, all the average tap pressures were averaged again per photo. These averages make it possible to compare means. The result is six variables in SPSS;

1. **Photo filename** - String, containing the photo filename for identification purposes.

2. **Valence** - Numeric, decimal value on a scale from 0.0-100.0.

3. **Arousal** - Numeric, decimal value on a scale from 0.0-100.0.

4. **Maximum tap pressure average** - Numeric, decimal value on scale from 0.0-6.67.

5. **Average tap pressure average** - Numeric, decimal value on scale from 0.0-6.67.

6. **Duration** - Numeric, decimal value in nanoseconds.

In other words, for every photo, there is a value for valence, arousal, maximum tap pressure average, average tap pressure average and duration.

Multiple linear regression

Testing for any correlation was completed with a multiple linear regression method. The advantage of this method is that both *duration* and *pressure* can be used as independent variables to check if there indeed is a relation to *valence* or *arousal* as dependent variables and that if there is a relationship, it also immediately produces a model to predict the dependent variables. A disadvantage of is that the relationship can not be checked for *valence* and *arousal* simultaneously, only for the separate variables.

What follows is four seperate multiple linear regression tests, two with *valence* as dependent variable, and two with *arousal* as dependent variable. Both dependent variables were tested for any relation ship with either *maximum tap pressure & duration* or *average tap pressure & duration*.

Before proceeding to the results, several assumptions needed to be considered before concluding that the data could be analyzed using multiple linear regression;

1. **Independence of observation** - Using Durbin-Watson to test for 1st-order autocorrelation. Value should be 2 ± 0.5.

2. **Linear relationships** - Visually inspecting a scatterplot of studentized residuals and unstandardized predicted values, and partial regression plots can indicate a (non-)linear relationship.

3. **Homoscedasticity of residuals** - Visually inspecting a scatter plot of studentized residuals and unstandardized predicted values to check if residuals are equal for all values of the dependent variable being predicted.

4. **No multicollinearity** - Inspection of correlation coefficients and Tolerance/VIF values for indication of correlation between independent variables.

5. **No unusual data points** - There should be no outliers, high leverage points or highly influential points.

6. **Normal distribution of errors** - Errors in prediction need to be normally distributed, otherwise determining significance can become problematic. By visually inspecting the histogram, Q-Q, and P-P plots.

All these assumptions are considered for every of the four separate multiple linear regression tests mentioned. Results of testing the assumptions are presented in the next section.

Additional study

Since tap duration has been measured as well, another small study will be added. It is not unlike the methods Essl et al. [7] describe, where they use tap finger surface area to infer pressure, except it will consider the relationship between tap pressure and tap duration, not tap pressure and tap finger surface area. Instead of multiple linear regression, it entails a regular linear regression. There are again several assumptions that should be considered before it can be concluded a linear regression is indeed the correct method to analyze the collected data. These assumptions are the same as for multiple linear regression, except multicollinearity testing, which is unnecessary in a study that contains two variables, and unusual data point testing, which is only assessed using casewise diagnostics, and not cook's or leverage values.

Dependent variable	Independent variables	d-w
Valence	Max. tap pressure, duration	2.086
	Avg. tap pressure, duration	2.094
Arousal	Max. tap pressure, duration	2.246
	Avg. tap pressure, duration	2.257

Table 1: Durbin-Watson values (d-w) outside of 2 ± 0.5 indicate autocorrelation issues.

RESULTS

This section presents the result on the two studies: the relation between tap pressure and emotion, and the relation between tap pressure and tap duration. The data that has been collected during the experiment and subsequently has been used for analysis can be found in Appendix Collected Data.

Tap pressure and emotion study

First, the results of checking each of the six assumptions are presented. The section Methods explains the necessity of considering these assumptions. Second, the multiple regression model is presented.

Independence of observation

As can be seen in Table 1, the Durbin-Watson values do not violate acceptable limits for each seperate test, indicating no autocorrelation.

Linear relationships

By visually inspecting scatter plots of the *unstandardized predicted value* against *studentized residuals* it can be assumed there is linearity. Furthermore, by looking at partial regression plots of each of the independent variables for every dependent variable, it is again apparent that there is an approximately linear relationship. See Appendix Linear Relationships and Homoscedasticity for the graphs used for inspection.

Homoscedasticity

Using the scatter plots of *unstandardized predicted value* against *studentized residuals* for inspection, the random spread of values indicate homoscedasticity of values. See Appendix Linear Relationships and Homoscedasticity for the graphs used for inspection.

Multicollinearity

Inspection of correlation coefficients (Appendix Multicollinearity for full tables) show none of the correlations > 0.7. In Table 2, tolerance values are found. None of the tolerance values fall below the limit of 0.1.

Unusual data points

For each seperate test, *studentized residuals*, *Cook's Distances* and *Leverage values* were checked. There were respectively no cases outside 3 Standard Deviations (SDs), no distances > 1.0 and no values > 0.2 (Appendix Unusual Data Points for minimum and maximum values for each).

Normal distribution of errors

Visual inspection of histograms and P-P plots for each seperate test show no signs of significant violation of normality. (Appendix Normality for the inspected graphs and diagrams)

Dependent variable	Independent variables	Tolerance
Valence	Maximum tap pressure	.728
	Duration	.728
	Average tap pressure	.758
	Duration	.758
Arousal	Maximum tap pressure	.728
	Duration	.728
	Average tap pressure	.758
	Duration	.758

Table 2: Tolerance values < 0.1 indicate collinearty issues.

Findings

A multiple regression was run to predict either valence or arousal from maximum tap pressure and duration, or average tap pressure and duration. Table 4 shows the model summary of each of the four multiple linear regression tests, indicating that no model allows for significant prediction of valence or arousal, $p > .05$. Moreover, taking a look at Table 3, it can be seen that none of the separate independent variables significantly add to the prediction model. (See Appendix Regression Coefficients for detailed coefficient information)

Dependent variable	Independent variables	Significance
Valence	Intercept	.702
	Max. tap pressure	.353
	Duration	.761
	Intercept	.669
	Avg. tap pressure	.306
	Duration	.750
Arousal	Intercept	.925
	Max. tap pressure	.095
	Duration	.722
	Intercept	.985
	Avg. tap pressure	.131
	Duration	.830

Table 3: Regression variables and their significance towards contribution to the model. None of the variables show $p < .05$. However, note that for Arousal and Max. tap pressure the relation almost reached signigicance. This prompts further research into Max. tap pressure for use in Arousal measurements.

Tap pressure and tap duration study

Because of the smaller nature of this study, it will be described in less detail. First, the assumptions for maximum tap pressure are presented. Secondly, the assumptions for average tap pressure are presented. And finally, the findings for both tests are presented.

Maximum tap pressure and tap duration

The relationship between maximum tap pressure and tap duration shows strong signs of linearity by visually inspecting a scatterplot of tap duration against maximum tap pressure.

Predicted variable	Predictor variables	F(2, 57)	Adjusted R^2	Significance
Valence	Max. tap pressure, duration	.462	-.019	.632
	Avg. tap pressure, duration	.556	-.015	.577
Arousal	Max. tap pressure, duration	1.632	.021	.204
	Avg. tap pressure, duration	1.361	.012	.264

Table 4: Summary of main findings. It shows that none of the models allow for significant prediction of valence or arousal, $p > .05$. Note the negative Adjusted R^2 values that indicate that those variables do not contribute in any way to the linear regression model.

Residuals show independence as assessed by a Durbin-Watson statistic of 2.223 and there were no outliers observed outside 3 SDs. Homoscedasticity was established as was inspected visually with a scatterplot of standardized residuals against standardized predicted values. A histogram of standardized residuals shows an approximately normal distribution, as is further proved with visual inspection of the P-P plot.

Average tap pressure and tap duration

Again, by visually inspecting a scatter plot of tap duration against average tap pressure, there is a strong indication of linearity. The Durbin-Watson statistic of 2.275 shows no signs of autocorrelation, there were again no outliers outside 3 SDs. Homoscedasticity was established as was inspected visually with a scatterplot of standardized residuals against standardized predicted values. A histogram of standardized residuals shows an approximately normal distribution, as is further proved with visual inspection of the P-P plot.

Findings

Table 5 shows a summary of the results. Tap duration statistically significantly predicted maximum tap pressure, F(1, 58) = 18,495, $P < 0.0005$. Furthermore, the linear regression model shows that the tap duration coefficient is statistically significant in the model ($p < 0.0005$, See Appendix), resulting in (1) in order to predict tap pressure from tap duration:

$$max\,tap\ pres. = -.169 + (6.522 * 10^{-9} * tap\,duration) \quad (1)$$

$$avg\,tap\ pres. = -.082 + (4.274 * 10^{-9} * tap\,duration) \quad (2)$$

Tap duration also statistically significantly predicted average tap pressure, F(1, 58) = 21,715, $P < 0.0005$. Furthermore, the linear regression model shows that the tap duration coefficient is again statistically significant in the model ($p < 0.0005$), resulting in equation (2) to predict average tap pressure from tap duration.

DISCUSSION

The main purpose of this research is to discover if there is a meaningful and significant relationship between tap pressure on a touchscreen and emotion. Using a quantitative approach with a sample size of 51 and multiple linear regression to explore this possible relationship, first results interestingly indicate no significant relationship. The secondary objective was to explore a relationship between tap pressure and tap duration, which is indeed the case; there is a significant relationship between tap duration and both maximum tap pressure and average tap pressure.

Evaluation of findings

Taking into regard hypothesis H_0, Table 4 show us that none of the tests create a significant model, $p < .05$. Therefor, hypothesis H_0 is accepted, and conversely hypothesis H_1 is rejected. One of the indicators why the null hypothesis is accepted lies with the adjusted R^2. For valence tests R^2 values are negative, -.019 and -.015. This occurs when the model contains independent variables (*tap pressure*, *duration*) that do not contribute to a prediction of the dependent variable (*valence*). For arousal tests R^2 is barely positive, .021 and .012. While this indicates that the independent values do contribute to a prediction (in contrast with negative R^2), it only does so very slightly. The values show that the independent variables (*tap pressure*, *duration*) only explain 2.1% and 1.2% of the variability of the dependent variable (*arousal*). Interestingly, these findings are in direct opposition to the findings of Lv et al. [14], where there is a direct correlation between pressure and emotion. It leads to believe that there are some factors in the experiment set up are not taken into account or applied erroneously.

The results from the study of a relationship between tap pressure and duration do show a significant association, however. Both for the maximum tap pressure and average tap pressure, the tap duration is a significant predictor in the linear regression model. It implies that pressure sensitive touchscreens might not be necessary, as tap pressure can be inferred from tap duration. However, tap pressure is likely not the only application of pressure sensitive touchscreens, so the development of those touchscreens could still prove valuable for future products.

Weaknesses

One weakness in the experiment design that could influence the result is the random order of presentation of pictures. Every participant was shown 60 pictures in random order, and the rationale of it was to eliminate any unintentional side effect of several pictures eliciting the same emotion and in their turn strengthen or weaken the emotional response. However, this also implicates that none of the executed experiments were fully comparable.

Another possible weakness is again related to implementing randomness into the design. The grid overlay that was shown on every picture was also randomly generated to negate the

Predicted variable	Predictor variable	F(1,58)	Adjusted R^2	Significance
Max. tap pressure	Duration	21.715	.26	$> .0005$
Avg. tap pressure	Duration	18.495	.229	$> .0005$

Table 5: Summary of secondary findings. It shows that that both models allow for significant prediction of both maximum tap pressure and average tap pressure, $p < .0005$

effects of the position of the tap on the screen. This was decided for because, with enough measurements, the position of the tap starts to have less impact on tap pressure if the position is random. Giving participants the same grids for the same photo might produce other results that do show significance.

Furthermore, this research assumes that every individual has the same physical response to emotional elicitation. In other words, it assumes that each person will exert a specific amount of pressure on a touchscreen from a set baseline rather than taking into account individual differences.

Finally, there might be a problem with the pressure detection. The range of pressure that can be detected with the used pressure sensitive touchscreen is 0.0 to 6.67. However, Appendix Collected Data shows that all the measured averaged pressures do not exceed .5, meaning that the experiment only used a fraction of the measurable range possible.

Recommendations

If one is to venture into further research for this topic, I would suggest to first try and repeat this experiment without the randomization that has been in place. Furthermore, rather than assuming every individual to respond the same to emotional elicitation and expecting a linear correlation, underlying patterns can be discovered. Especially looking for patterns specific to the participant rather than trying to find a general pattern for the population. A suggestion to discover such patterns is the use of self-assessment as a methodology. Self-assessment by participants makes it possible to link tap pressure data to how the participant is feeling, rather than assuming a baseline set by visual stimuli. However, perhaps most importantly, the use of a pressure sensitive touchscreen that has a range more in line with tap pressure (0.0 to 1.0 for example) and higher sensitivity (smallest change that can be detected) could improve the results.

Conclusion

Though there are several indications for a relationship between tap pressure and emotion, this study is inconclusive on the results. With the rejection of the H_1 hypothesis, it is uncertain if tap pressure is linked to emotional state of the user. However, the literature review still highlights the importance of emotion detection by computers and argues that current methods do not yet suffice for deployment on a larger scale. This is partly the reason why the study of the relationship between tap duration and tap pressure has been added. It shows that tap duration can significantly predict maximum and average tap pressure and that tap duration could be another predictor for emotional state. Furthermore, this enables the use of regular touchscreens for pressure detection.

There are still many things to discover in the field of affective computing before the smartphones in our pockets can love their users back, but the continuous stream of research is gaining solid ground into making this future vision into a reality. It is a reality where the personal smart devices can be of even better assistance, but also make better decisions for what the user is trying to achieve. One possibility could be that a telecom provider app or website can contact customer support in the background already when it notices the user is upset about their bill. Another interesting case would be music applications promoting new and exciting songs when the user is happy, but slowed down and calm songs when the user is relaxed. Alternatively, games that have characters that can be helpful and friendly when progression is stalling, but can also suitably respond to aggression and anger, mitigating frustration or escalation. As a final example, educational systems that can detect if the user is getting frustrated can provide additional examples, or when it notices boredom can provide more challenging exercises.

I still believe there is a strong need for ubiquitous and non-invasive procedures for detecting emotion with smart devices. After performing this study on the use of pressure sensitive touchscreens I can only urge others to explore other ways of achieving the same goal, either by replicating this study with adaptations or discovering entire new ways of non-invasive emotion detection.

ACKNOWLEDGMENTS

I thank all the people of this study for their effort, time and patience during their participation in the experiment. Furthermore, I want to show my gratitude towards Dan Buzzo for his excellent supervision, and Frank Nack, for his time and feedback as second assessor. Finally, I want to thank Mariëlle for her loving support throughout the study.

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APPENDIX

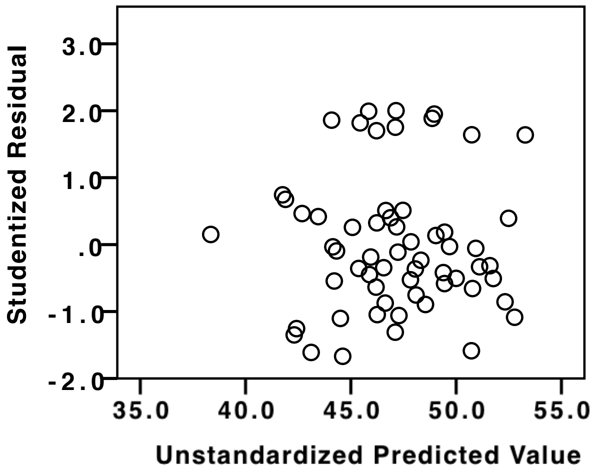
COLLECTED DATA

Filename	Valence	Arousal	Time	Avg. tap pressure	Max. tap pressure avg.
A022	24.95	53.276	89393583.8	0.298464877	0.416491228
A024	42.079	47.688	84554533.62	0.300806132	0.413709677
A030	3.492	74.032	87996838.71	0.304178858	0.425607639
A042	15.551	66.332	92436313.4	0.305231753	0.425384615
A054	31.094	65.351	92361315.21	0.319874056	0.446335079
A061	21.038	41.819	85117894.48	0.290563073	0.401832461
A082	34.795	54.998	90037148.75	0.308932455	0.42457483
A084	21.07	63.252	90149839.94	0.304433932	0.414786325
A105	30.428	43.906	88443661	0.30125502	0.415811966
A120	12.011	71.41	86406374.25	0.273470976	0.37425829
H002	34.785	57.825	88850316.24	0.290741877	0.40546875
H024	39.573	37.783	90457494.14	0.279637045	0.383164983
H028	37.557	46.953	88616478.38	0.285222469	0.388601036
H042	53.671	51.888	90541183.91	0.325679551	0.444500846
H047	44.436	38.656	90053837.91	0.300899043	0.414746946
H049	31.626	52.99	87026164.88	0.271526233	0.365059222
H054	43.978	40.317	89983105.51	0.278912834	0.382393162
H085	49.555	41.463	87056573.8	0.273131726	0.375388601
H110	42.523	45.154	88067865.48	0.289302065	0.398653199
H122	3.675	83.936	88886576.45	0.317968396	0.440221088
N008	59.745	22.977	89808099.51	0.330454416	0.453931624
N013	61.967	10.196	86586561.1	0.264292438	0.362041885
N015	54.05	29.756	88751677.94	0.28629579	0.393162393
N026	43.063	20.506	90055559.1	0.280169104	0.386294416
N030	59.194	24.2	90756137.54	0.305817412	0.421827411
N080	59.67	20.826	92993731.9	0.308424986	0.425
N085	53.586	26.136	85262989.43	0.287760335	0.395656028
N087	48.873	30.279	89308919.38	0.292517287	0.407155323
N091	53.994	12.065	89020520.85	0.326457954	0.443923611
N104	57.932	32.797	86435663.47	0.319300163	0.439179756
P004	90.464	19.615	89564050.94	0.307675967	0.425906736
P012	88.264	27.812	90319127.29	0.302369259	0.423281787
P014	95.341	20.78	90103201.27	0.2941746	0.402991453
P024	90.101	21.514	91224531.52	0.303101109	0.420408163
P026	96.371	11.431	86531449.21	0.294100221	0.401036269
P033	96.202	15.369	85145295.63	0.275990741	0.382051282
P041	94.457	12.363	86086636.52	0.297754255	0.408762887
P065	89.822	43.095	89951698.59	0.308912895	0.437434555
P093	90.874	12.318	86754564.39	0.273943272	0.375561313
P108	92.636	17.15	87882749.86	0.259960519	0.361505922
Sn012	26.584	70.282	87923003.91	0.262485272	0.365378007
Sn016	17.437	67.823	90813583.01	0.312752004	0.437893864
Sn029	29.537	61.545	86735793.8	0.283886277	0.394885362
Sn042	39.296	57.314	84738651.2	0.282440996	0.386998255
Sn053	48.984	43.858	91606129.34	0.292613029	0.403083333
Sn084	43.324	49.545	87405318.93	0.317473039	0.426615646
Sn087	37.985	62.147	89243886.29	0.306568907	0.41640625
Sn089	52.395	43.782	89792211.52	0.289817937	0.4004363
Sn102	41.817	72.416	90919701.05	0.341122118	0.483503401
Sn122	41.341	57.473	90406835.68	0.312604952	0.425673401
Sp023	51.451	41.216	89392134.05	0.309397068	0.427891156
Sp046	35.729	47.421	83648634.84	0.27277924	0.372368421
Sp051	12.158	74.854	87254606.89	0.31828541	0.438656195
Sp055	26.366	58.479	87970734.52	0.294080347	0.396649485
Sp078	36.595	43.045	90907493.28	0.313341706	0.431887755
Sp104	56.83	53.19	88734835.47	0.299041227	0.411941581
Sp115	39.052	69.371	87878911.43	0.284081438	0.390034364
Sp122	34.757	64.406	86505137.93	0.271380253	0.374265976
Sp136	9.521	78.436	90110763.95	0.328360271	0.451128472
Sp140	54.253	47.416	90283857.72	0.302580775	0.423044218

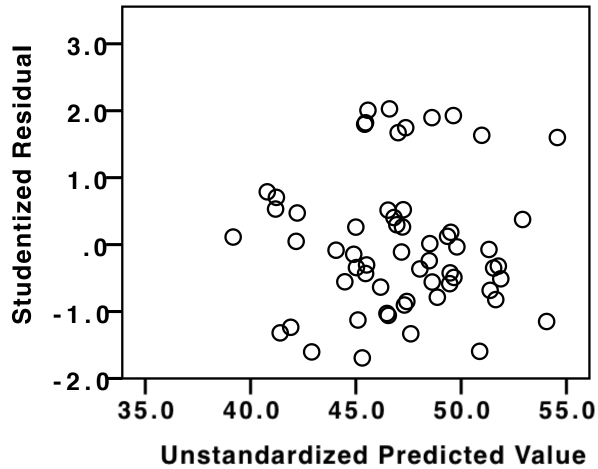
Table 6: The collected data that is used for analysis. Data on tap pressure and duration has been collected from 51 participants, that performed four taps for 60 photos.

LINEAR RELATIONSHIPS AND HOMOSCEDASTICITY

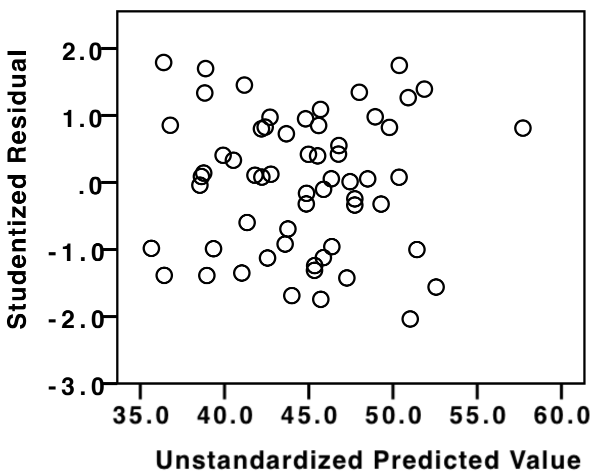
Scatter plot: unstandardized predicted value vs. studentized residuals



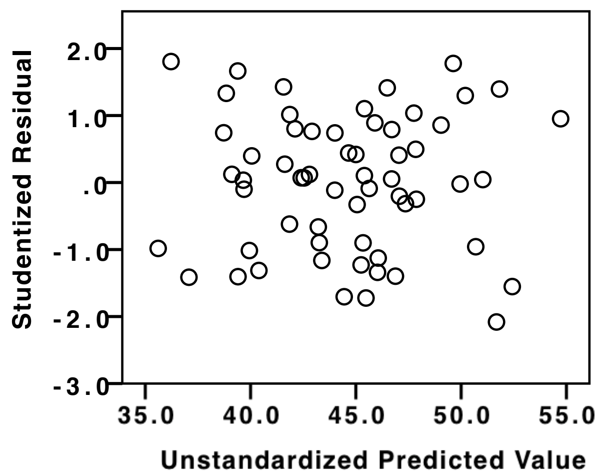
(a) Related to test of valence, maximum pressure, and tap duration.



(b) Related to test of valence, average pressure, and tap duration.



(c) Related to test of arousal, maximum pressure, and tap duration.



(d) Related to test of arousal, average pressure, and tap duration.

Figure 5: Scatter plots of predicted values against studentized residuals. Note that because of randomness of data points, linearity can still be assumed. There is no indication of issues with homoscedasticity because there does not seem to be a funnel or fan shape.

Partial regression plots

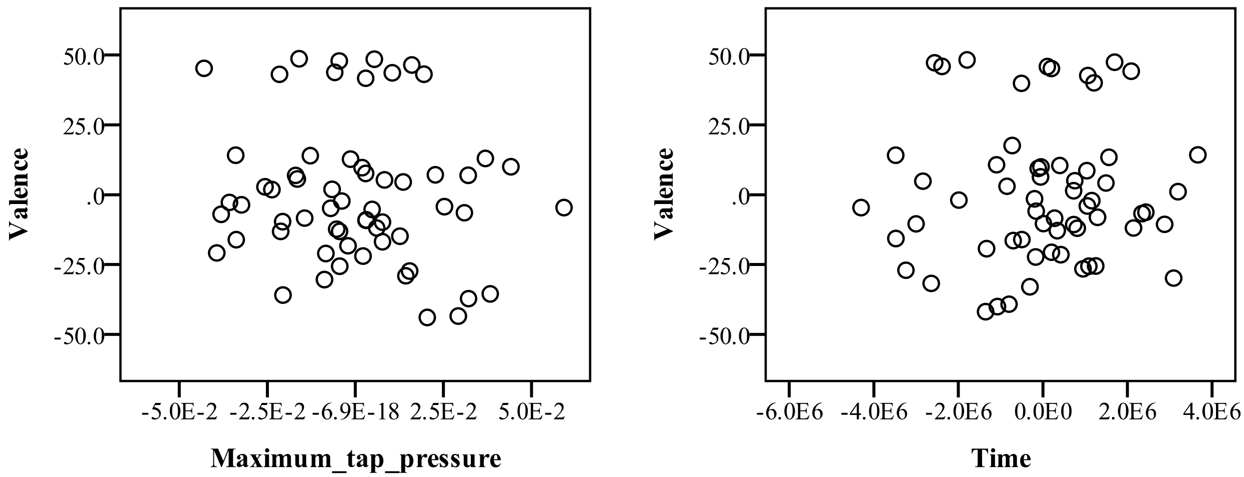


Figure 6: Partial regression plots with valence (dependent variable), maximum pressure and duration (independent variables). Note that the randomness of data points allows for the assumption of approximate linearity.

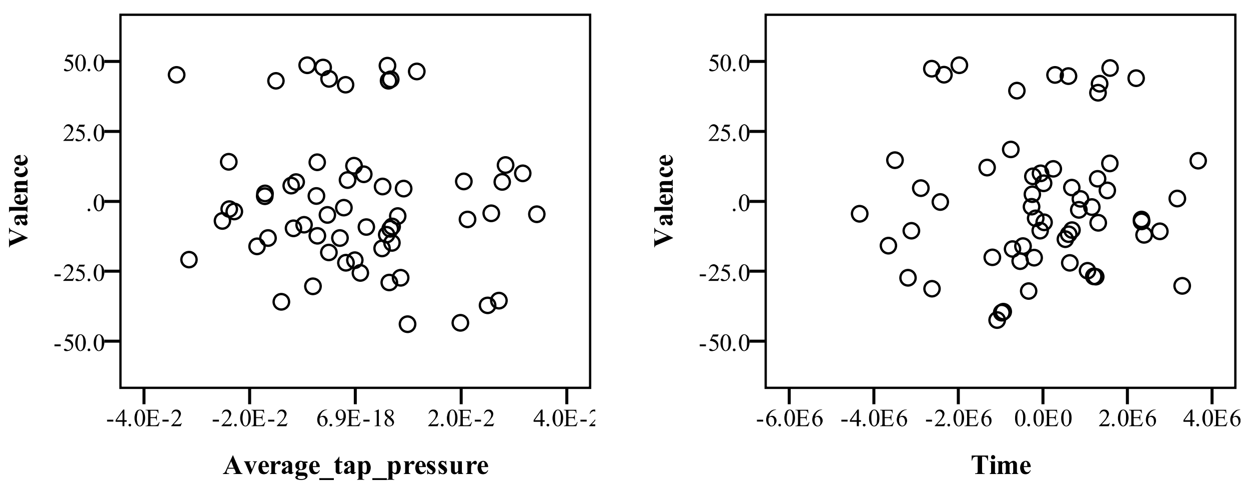


Figure 7: Partial regression plots with valence (dependent variable), average pressure and duration (independent variables). Note that the randomness of data points allows for the assumption of approximate linearity.

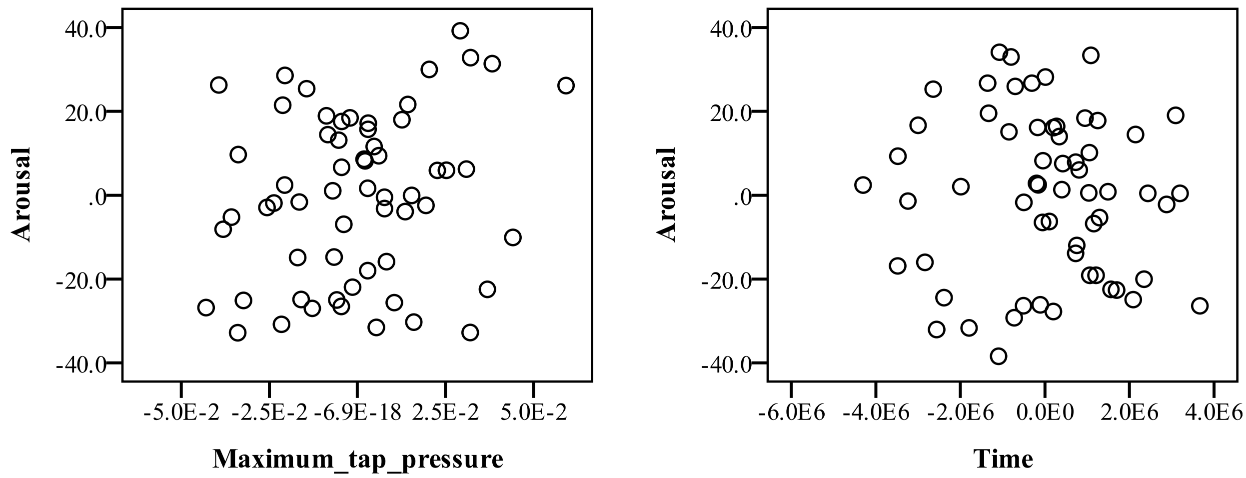


Figure 8: Partial regression plots with arousal (dependent variable), maximum pressure and duration (independent variables). Note that the randomness of data points allows for the assumption of approximate linearity.

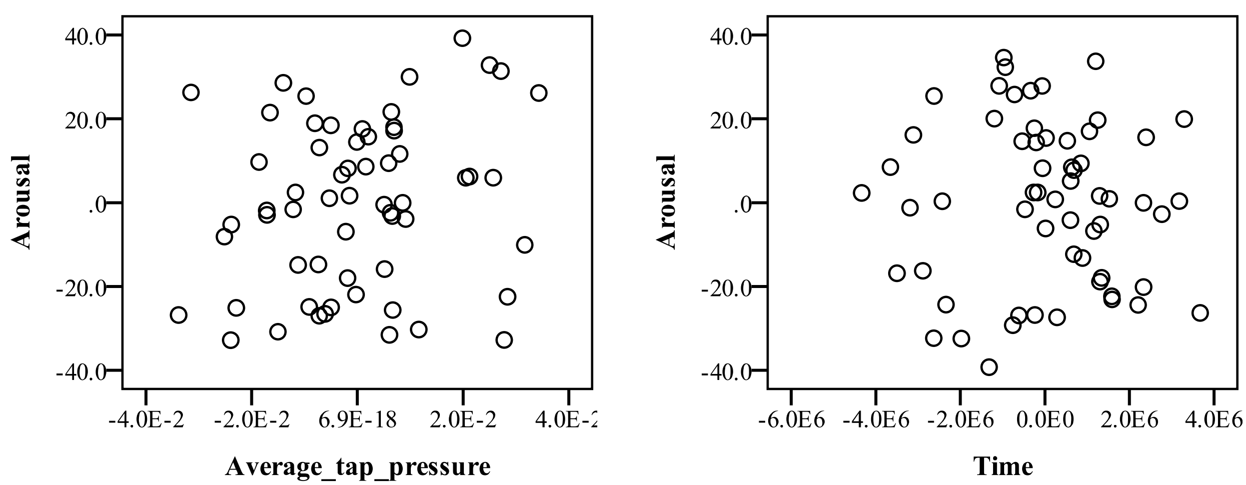


Figure 9: Partial regression plots with arousal (dependent variable), average pressure and duration (independent variables). Note that the randomness of data points allows for the assumption of approximate linearity.

MULTICOLLINEARITY

		Valence	Duration	Max. tap pressure
Pearson Correlation	Valence	1.000	-.028	-.120
	Duration	-.028	1.000	.522
	Max. tap pressure	-.120	.522	1.000
Sig. (1-tailed)	Valence	.	.415	.181
	Duration	.415	.	.000
	Max. tap pressure	.181	.000	.

Table 7: Correlations of valence, maximum tap pressure and tap duration. VValues do not exceed limits, > .7, except when variables are compared to themselves, which can be safely be ignored.

		Valence	Duration	Avg. tap pressure
Pearson Correlation	Valence	1.000	-.028	-.132
	Duration	-.028	1.000	.492
	Avg. tap pressure	-.132	.492	1.000
Sig. (1-tailed)	Valence	.	.415	.158
	Duration	.415	.	.000
	Avg. tap pressure	.158	.000	.

Table 8: Correlations of valence, average tap pressure and tap duration. Values do not exceed limits, > .7, except when variables are compared to themselves, which can be safely be ignored.

		Arousal	Duration	Max. tap pressure
Pearson Correlation	Arousal	1.000	.080	.228
	Duration	.080	1.000	.522
	Max. tap pressure	.228	.522	1.000
Sig. (1-tailed)	Arousal	.	.272	.040
	Duration	.272	.	.000
	Max. tap pressure	.040	.000	.

Table 9: Correlations of arousal, maximum tap pressure and tap duration. Values do not exceed limits, > .7, except when variables are compared to themselves, which can be safely be ignored.

		Arousal	Duration	Avg. tap pressure
Pearson Correlation	Arousal	1.000	.080	.212
	Duration	.080	1.000	.492
	Avg. tap pressure	.212	.492	1.000
Sig. (1-tailed)	Arousal	.	.272	.052
	Duration	.272	.	.000
	Avg. tap pressure	.052	.000	.

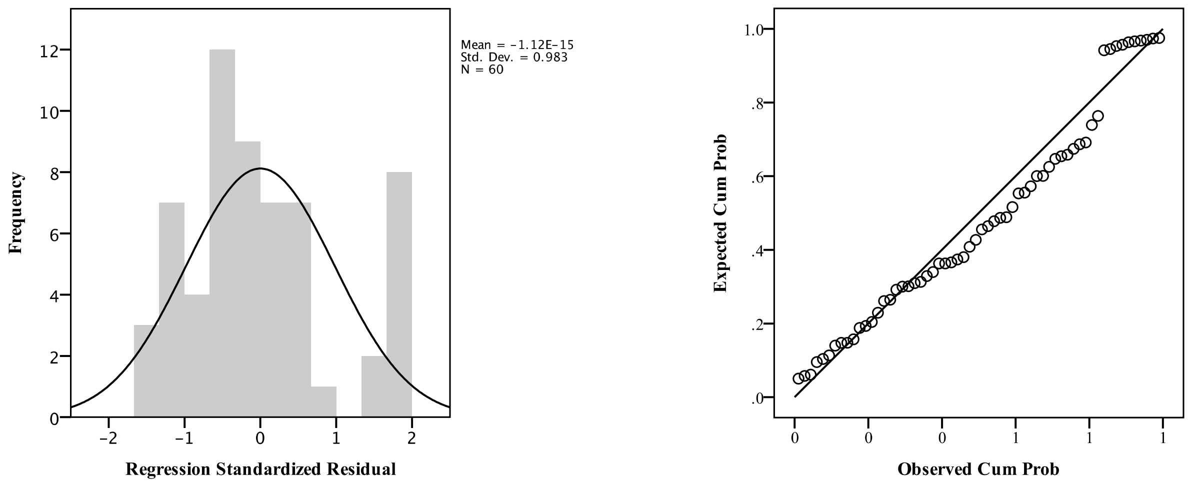
Table 10: Correlations of arousal, average tap pressure and tap duration. Values do not exceed limits, > .7, except when variables are compared to themselves, which can be safely be ignored.

UNUSUAL DATA POINTS

Dependent variable	Independent variables	Studentized residuals		Cook's Distance		Leverage values	
		Min	Max	Min	Max	Min	Max
Valence	Max. tap pressure, duration	-1.7	2.06	.0	.09	.0	.14
	Avg. tap pressure, duration	-1.72	2.09	.0	.09	.0	.1
Arousal	Max. tap pressure, duration	-2.1	1.83	.0	.08	.0	.14
	Avg. tap pressure, duration	-2.15	1.84	.0	.11	.0	.1

Table 11: Studentized residuals, Cook's values and leverage values. Studentized residuals are between -3 and +3 SDs. Cook's Distance values are < 1. Leverage values are $< .2$. There is no indication of highly influential points.

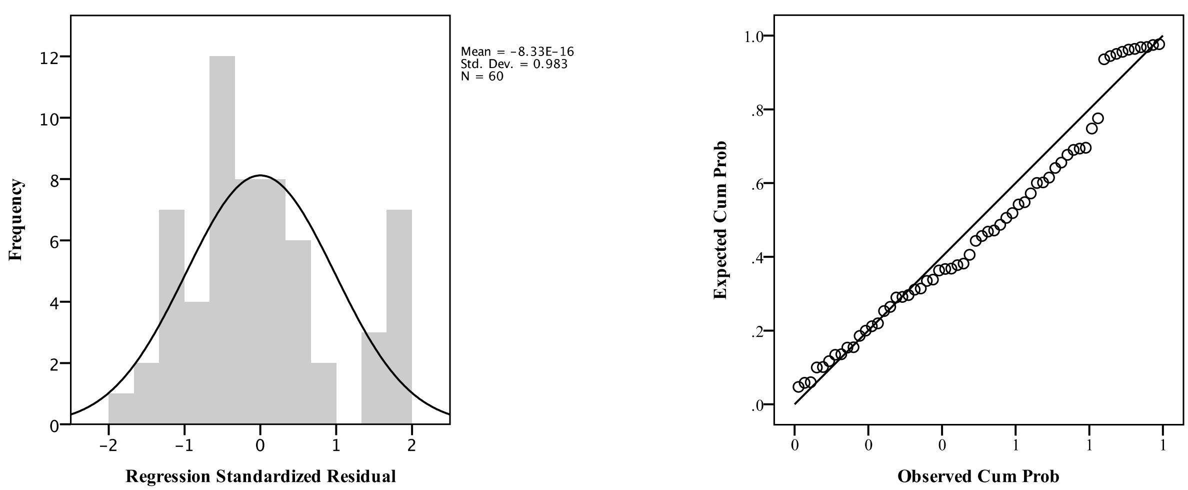
NORMALITY



(a) Histogram

(b) P-P plot

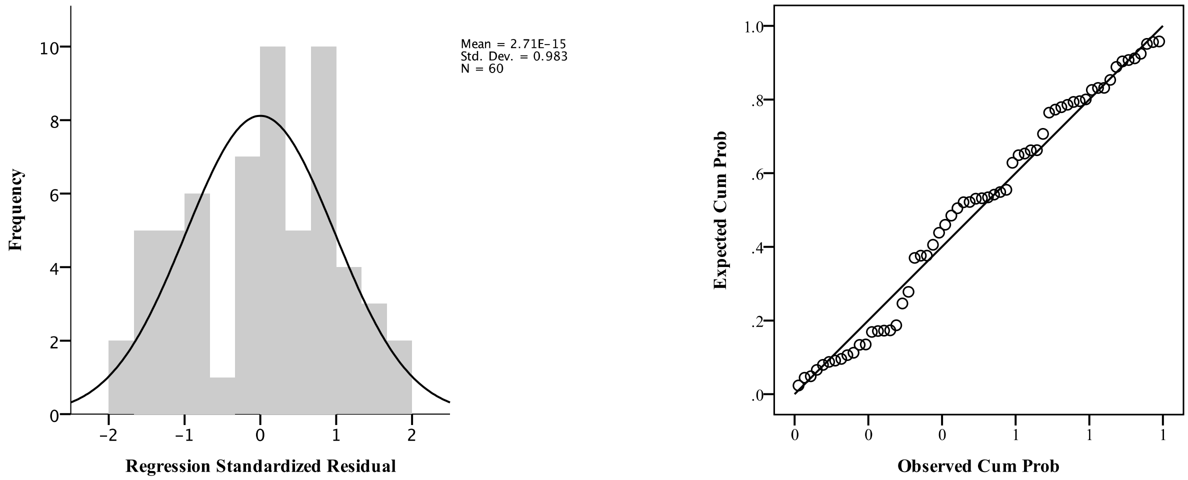
Figure 10: Normality graphs for valence, maximum tap pressure and duration. The histogram shows an approximate normal distribution, with a spike at +2 SD. The P-P plot shows little deviation from the origin line, so normal distribution of samples can safely be assumed



(a) Histogram

(b) P-P plot

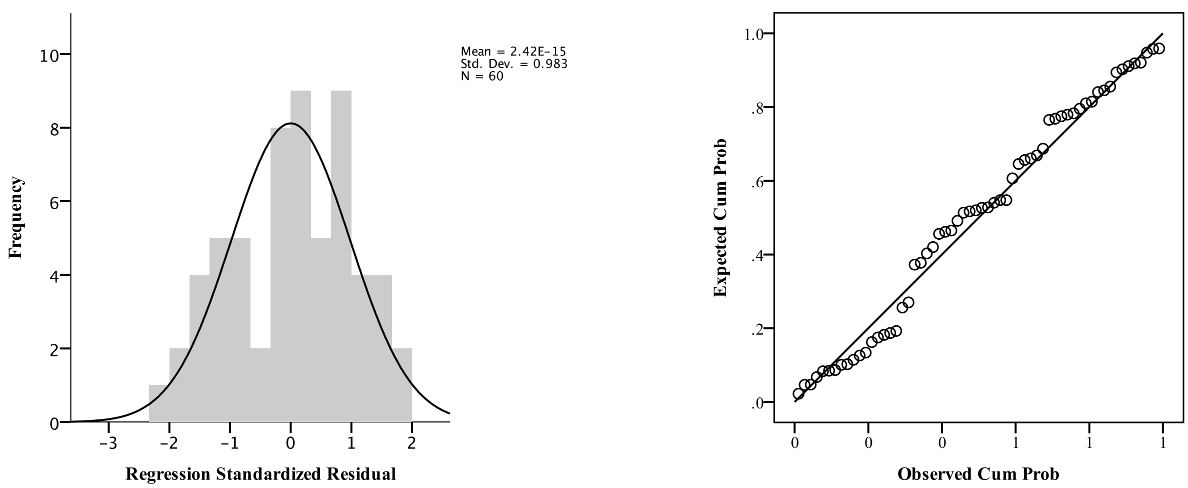
Figure 11: Normality graphs for valence, average tap pressure and duration.The histogram shows an approximate normal distribution, with a spike at +2 SD. The P-P plot shows little deviation from the origin line, so normal distribution of samples can safely be assumed



(a) Histogram

(b) P-P plot

Figure 12: Normality graphs for arousal, average tap pressure and duration. The histogram shows an approximate normal distribution with a striking dip at -.5 SD. However, the P-P plot shows little deviation from the origin line and leads to the safe assumption of a normal distribution of samples.



(a) Histogram

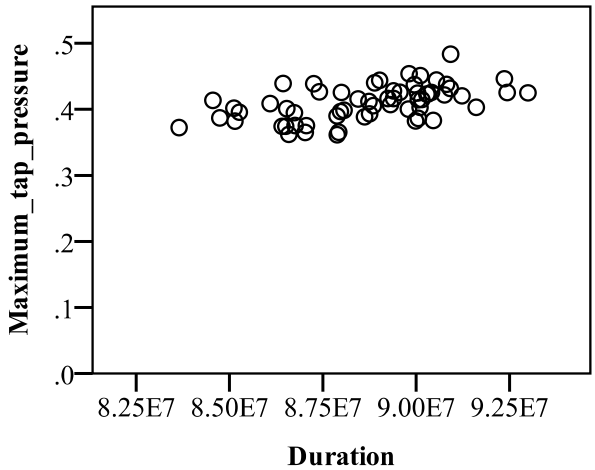
(b) P-P plot

Figure 13: Normality graphs for arousal, average tap pressure and duration. The histogram shows an approximate normal distribution with a striking dip at -.5 SD. However, the P-P plot shows little deviation from the origin line and leads to the safe assumption of a normal distribution of samples.

REGRESSION COEFFICIENTS

Dependent variable	**Independent variable***	B	SE_b	β	*Significance*
Valence	Intercept	53.722	139.848	n.a.	.702
	Max. tap pressure	-136.476	145.694	-.144	.353
	Duration	$5.566e^{-7}$	.000	.047	.761
	Intercept	59.459	138.468	n.a.	.669
	Avg. tap pressure	-211.353	204.722	-.156	.306
	Duration	$5.698e^{-7}$	.000	.048	.750
Arousal	Intercept	10.397	109.668	n.a.	.925
	Max. tap pressure	193.809	114.182	.256	.095
	Duration	$-5.1e^{-7}$	.000	-.054	.722
	Intercept	-2.076	109.254	n.a.	.985
	Avg. tap pressure	247.231	161.530	.227	.131
	Duration	$-3.027e^{-7}$	.000	-.032	.830

Table 12: Regression coefficients table with significance. B = Unstandardized coefficient. SE_b = Std. Error. β = Standardized coefficients. Significance = p-value. **Note*: Intercept should not be regarded as independent variable.



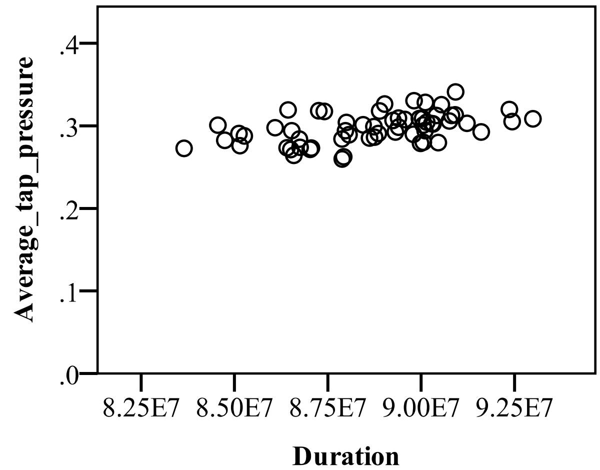
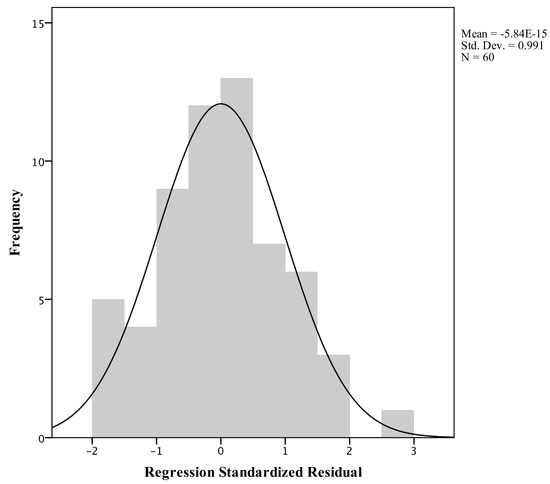
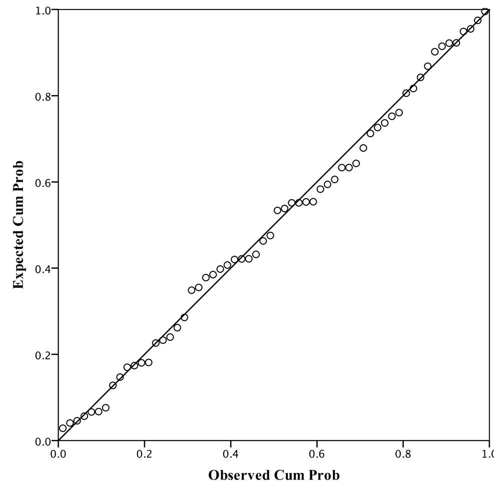


Figure 14: Linearity assessment graphs for max. tap pressure (left) and avg. tap pressure (right). It shows a scatter plot of tap pressure against tap duration. Both graphs show a strong sign of linearity.

SECONDARY STUDY - NORMALITY

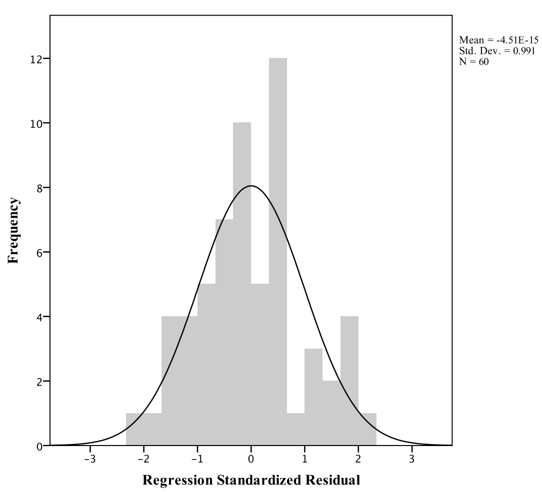


(a) Histogram

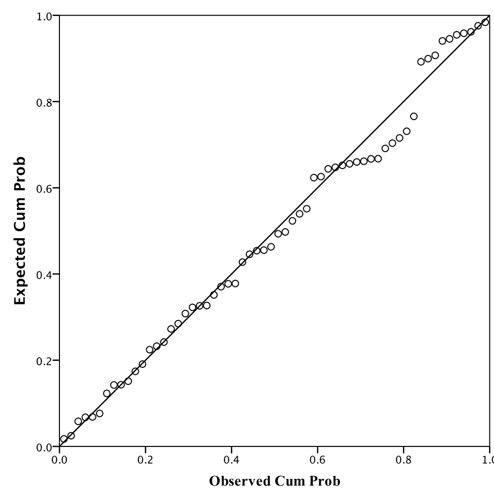


(b) P-P plot

Figure 15: Normality graphs for max. tap pressure and duration. The histogram shows an approximate normal distribution. The P-P plot shows little deviation from the origin line, further proving a normal distribution of samples.



(a) Histogram



(b) P-P plot

Figure 16: Normality graphs for avg. tap pressure and duration. The histogram shows an approximate normal distribution. The P-P plot shows little deviation from the origin line except at the top right, where it deviates a little more. Still, the deviation is not large enough to warrant any concerns over normal distribution of samples.

SECONDARY STUDY - REGRESSION COEFFICIENTS

Dependent variable	**Independent variable***	B	SE_b	β	*Significance*
Max. tap pressure	Intercept	-.169	.124	n.a.	.180
	Duration	$6.552e^{-9}$	.000	.522	$> .0005$
Avg. tap pressure	Intercept	-.082	.088	n.a.	.357
	Duration	$4.274e^{-9}$	.000	.492	$> .0005$

Table 13: Regression coefficients table with significance. B = Unstandardized coefficient. SE_b = Std. Error. β = Standardized coefficients. Significance = p-value. **Note*: Intercept should not be regarded as independent variable.