

USE OF EMOTION IN DESIGNING BI DASHBOARDS

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Abstract: Due to increased focus on user experience and user interface optimization for users and customers, this trend leads to new methods for UX improvements. One of the methods is the use of emotion for getting additional feedback for UX designers. In this paper, we focused on finding relations among emotions, appearance, clarity, time, and a number of elements to improve Business Intelligence dashboards.

Keywords: UX – User Experience, UI – User Interface, BI – Business Intelligence, Designing BI dashboards, BI dashboards

1 INTRODUCTION

Using emotion in improving UX (user-experience) and adding value to development has been proven [3] [14] [15]. By nature, emotion drives human actions and decisions [16]. Using emotion in UX also contributes to the trend of using emotion in marketing [13]. UX is also considered as part of the marketing discipline. Improving the UX of any product has been proven to increase customer satisfaction and user satisfaction, leading to increased revenue, lower marketing costs, and justifying the return of the investments into better UX [10]. Also, better UX can increase the efficiency of employees [7].

Trends such as data analysis are booming not just in Business Intelligence (BI) but also in process mining, AI data automation, and others. This trend is booming due to the exponential growth of data, which can be related to Moore's law.[1]

Emotions are complex phenomena and are characterized by their high sensitivity and variability. The sensitivity of emotions to changes in personal, situational circumstances is reflected in the fact that emotions themselves can change without apparent changes in objective circumstances (based on a subjective assessment of the situation). In one situation, the emotions may be aroused, but not in another. [9]

Research supposes companies want to improve the UX of their BI dashboards to increase the efficiency of their employees or customers. Companies can use general UX designing methods for improving the UX, which has already been demonstrated in previous research [5]. Nevertheless, the traditional methods of measuring UX, such as eye-tracking, focus on measuring the manifestative effects of UX rather than the actual sentiment the system triggers. Therefore, in this paper, we focus on the sentimental analysis of UX. We believe that using emotion recognition software may help to speed up the process of software interface testing and, moreover, bring more precise results than other UX methods.

Most scientific articles focus on using emotions to express whether the user liked the product or not and whether the user is keen to use it further. [11] However, these studies do not mention how these emotions change in relation to the interface features such as the number of components, the use of white space or layout. In this paper, using FaceReader, the software for emotion recognition, we analyse how emotions can be used to formulate general design rules for Business Intelligence software. FaceReader is the most cited software worldwide for

emotion recognition [4]. FaceReader recognizes Ekman's basic emotions, which include happiness, sadness, anger, surprise, fear, disgust and contempt [6]. FaceReader recognizes just the first six emotions from Ekman's seven basic emotions.

This paper aims to explore the possibility of using emotion recognition software to test user-friendliness during software development. To verify our hypotheses, we analyze the relationships between the User Experience and User Interface heuristics such as the number of elements, appearance, clarity, emotions and time necessary to complete defined tasks when testing various designs of the business intelligence dashboard. This study assumes that better UX & UI design is related to positive emotions such as happiness. Also, we suppose that confusing and ugly UX & UI designs can trigger negative emotions like sadness, anger, fear and disgust.

2 METHODOLOGY

This research is focused on revealing the dependencies among the number of elements, appearance, clarity, emotions, time, and various designs of business intelligence dashboards. Six different drafts (business intelligence dashboards) were selected with different designs, number of elements, colours, and indicators in the draft. It was most often a combination of tables, graphs, and numerical indicators. Two of the six images were specific in that they were drafts designed in spreadsheet software. The drafts are different in design; (draft 2) was a cleaned spreadsheet without colours, bold text, italics, or other graphic elements. The second table (draft 3) had precisely the same data, but graphic elements were used, such as bold text for headings and colours to separate the size of values. The number of elements in the draft was calculated for each draft. Numerical, graphic, and textual elements from the design were included in the elements.

The participants' tasks were to find two numerical values in all six drafts and say them aloud after finding them. The participants had never seen the drafts before, so the experiment results are coherent. Also, due to the coherence of the data, each participant had a randomly generated sequence of drafts and with the increasing number of repetitions, due to the "Law of Exercise"¹, participants could improve their ability to find values in the draft [8].

All research was conducted remotely due to the covid-19 pandemic. The whole experiment took place via the ZOOM platform. The experiment was recorded using an OBS studio for recorded computer areas and a webcam shot of each participant. Each participant's face was recorded for emotion analysis. The FaceReader software analysed manifestations of the participants' emotions from the recording. For the experiment, 20 participants from the field of management informatics across the bachelor's and master's degree programs were randomly selected. The population of all possible participants was 92 students. The age range of students was from 19 to 26 years.

For the experiment process, a date for the experiment interview was agreed on with every participant. The interviews were conducted online on the ZOOM platform. At the beginning of the interview, each participant was asked their age, gender, and questions that were not related to the experiment to put them at ease, so that each participant's emotions were as coherent as possible. It was also checked whether the participant had an adequately set up webcam that captured the entire face. Subsequently, a link to dashboard drafts was sent to the participant. Then the participant started sharing his screen and was instructed to open the first draft. Then the first question was read. After answering the first question, a second question was asked. This process was repeated for all drafts. The participant was timed for each draft,

¹ Law of Exercise – people get better with every repetition of some activity.

and time started after reading the first question and turned off after the second answer was heard. All six proposals were examined in this way. The last part of the interview was to score the appearance and clarity of the drafts. Every participant in the last part was asked to rate the appearance and clarity of each draft. Participants rated the drafts on a scale from 1-10, where 10 was the best score.

Subsequently, recorded images of participants' faces were analysed by FaceReader software. The data analysis was performed in JupyterLab. The correlation function in the Jupyter environment was used for the analysis of dependencies.

3 RESULTS

Table 1 shows the measured data for each BI dashboard draft from the experiment. The metrics of appearance, time, and clarity are the average of all values from all participants. The values of emotions are the average of all values measured by FaceReader software from all participants. Finally, the number of elements represents how many elements are in the design.

Table 1: Collected data from participants

<i>Draft</i>	<i>Number of elements</i>	<i>Time</i> Ø	<i>Appearance</i> Ø	<i>Clarity</i> Ø	<i>Happy</i> Ø	<i>Sad</i> Ø	<i>Angry</i> Ø	<i>Surprised</i> Ø	<i>Scared</i> Ø	<i>Disgusted</i> Ø
Draft 1	223	33.25	4.9	4.35	0.104	0.049	0.100	0.028	0.011	0.039
Draft 2	215	22.55	3.45	5.75	0.094	0.059	0.080	0.021	0.024	0.043
Draft 3	215	17.4	5.1	6.7	0.079	0.054	0.116	0.020	0.025	0.024
Draft 4	159	18	7.2	7.3	0.074	0.049	0.055	0.028	0.014	0.027
Draft 5	42	14	8.925	8.85	0.152	0.038	0.067	0.019	0.016	0.037
Draft 6	173	22	7.1	6.7	0.060	0.058	0.074	0.029	0.020	0.026

A correlation matrix was created from the data in Table 1. Pearson correlation was used for the calculation. The results of the experiment are presented in Figure 1, where the individual dependencies of the metrics between each other can be seen. It can be seen from Figure 1 that the dependence between appearance and clarity is a high dependence with a correlation coefficient of 0.81. Furthermore, a very strong negative dependence between clarity and time was measured with a correlation coefficient of -0.93.

This means that poorer clarity correlates with a longer time to find the indicator in the proposal. A strong negative dependence was measured between clarity and the number of elements with a correlation coefficient of -0.87. Also, the number of elements negatively correlates with the appearance. The correlation coefficient is -0.88, where a higher number of elements negatively affects the appearance and also the clarity.

Dependencies between emotions and other metrics:

Happiness is negatively correlated with the number of elements and the coefficient -0.67; higher number of elements reduces user happiness. The dependence between happiness and appearance is weak, with a coefficient of 0.35. Between happiness and clarity, there is also a weak dependence with a value of 0.37. The relationship between time and happiness has not been measured.

Sadness is strongly correlated with the number of elements with a coefficient value of 0.78. The dependence between sadness and appearance is high and negative with a coefficient of -0.7. Between sadness and clarity, the dependence is negative and is moderately strong with a coefficient of -0.53. The relationship between sadness and time has not been measured.

Number of elements	1	0.65	-0.88	-0.87	-0.67	0.78	0.6	0.31	0.29	-0.026
Time	0.65	1	-0.56	-0.93	-0.19	0.29	0.36	0.53	-0.37	0.39
Appearance	-0.88	-0.56	1	0.81	0.35	-0.7	-0.59	0.053	-0.43	-0.35
Clarity	-0.87	-0.93	0.81	1	0.37	-0.53	-0.52	-0.4	0.077	-0.32
Happy	-0.67	-0.19	0.35	0.37	1	-0.81	-0.1	-0.61	-0.29	0.58
Sad	0.78	0.29	-0.7	-0.53	-0.81	1	0.25	0.29	0.61	-0.13
Angry	0.6	0.36	-0.59	-0.52	-0.1	0.25	1	-0.31	0.37	-0.1
Surprised	0.31	0.53	0.053	-0.4	-0.61	0.29	-0.31	1	-0.53	-0.24
Scared	0.29	-0.37	-0.43	0.077	-0.29	0.61	0.37	-0.53	1	-0.16
Disgusted	-0.026	0.39	-0.35	-0.32	0.58	-0.13	-0.1	-0.24	-0.16	1
	Number of elements	Time	Appearance	Clarity	Happy	Sad	Angry	Surprised	Scared	Disgusted

Figure 1: Results of experiment in the correlation matrix

Anger correlates with the number of elements, and the dependence is moderate with a value of 0.6. The angry emotion is negatively correlated with appearance and clarity. The strength of the dependence is medium, and the values are -0.59 and -0.52. A weak relationship between anger and time was measured with a value of 0.36.

Surprise correlates with time, and the value of correlation is 0.53. Surprise correlates with the number of elements with a value of 0.31. Furthermore, a negative dependence between surprise and clarity was found. The strength of the dependence is weak, with a value of -0.4. The relationship between surprise and appearance has not been measured.

The emotion scared negatively correlates with time, and the strength of dependence is weak with a value of -0.37. Scared negatively correlates with appearance. The value is -0.43. The relationships between scared, number of elements, and clarity were not measured.

Disgust correlates with time, and the dependence is weak with a value of 0.39. Disgust negatively correlates with appearance, and the size of the dependency is weak with a value of -0.35. Disgust further negatively correlates with clarity. The strength of the dependence is weak, with a value of -0.32. The relationship between disgust and the number of elements has not been measured.

4 DISCUSSION

In the research, we analyzed the relationships between the User Experience and User Interface heuristics such as the number of elements, appearance, clarity, emotions and time necessary to complete defined tasks when testing various designs of business intelligence dashboards. The experiment confirmed the assumption that good UX & UI design correlates with positive emotions and confusing and ugly UX & UI designs correlate with negative emotions. A similar hypothesis was tested in [17], where they analyzed if completing complex tasks on websites could trigger anger via FaceReader. The results of their research were similar; complicated

websites trigger the anger of users. Other research results [3] show that difficult and complex UI is hard to use and negatively influences the users' emotions. This provides further evidence to prove the results of this paper in that a higher number of elements and lower clarity trigger users' negative emotions like anger, sadness, disgust or fear.

Face recognition of emotion was reviewed and studies were conducted to validate if the results of face recognition software are reliable. Research papers focused on FaceReader indicate some limitations on the side of FaceReader and on the side of the environment's set-up, which can influence the results. The results in [12] point out the importance of the priming participants because priming influences measurement by FaceReader. Nevertheless, results from FaceReader in most cases match with participants' feeling during self-assessment. Similar conclusions are reported in [2]. The research in [18] shows that FaceReader has a statistically significant deviation compared to other methods of tracking emotion like EMC, but in self-assessment comparison there were no statistically significant differences in results compared to FaceReader. These papers show there can be inaccuracies in measuring emotions. However, none of the research proves high inaccuracy and, in most cases, FaceReader provides reliable results. Minor inaccuracies are also eliminated by a higher number of participants. In the research conducted here, 20 participants were involved, which we consider as reputable to mitigate inaccuracies caused by priming of participants or FaceReader.

5 CONCLUSION

The results confirmed that metrics connected with good UX & UI positively influence the emotion of the user. On the other hand, metrics connected with confusing and ugly UX & UI negatively influence the users. There is the correlation among metrics such as number of elements, appearance, clarity, and time to complete certain tasks and emotions.

Research conducted on a similar topic confirmed analogous results to this research. Thanks to these findings, it is possible to make a few recommendations for designing and optimizing BI dashboards. If people say that a proposal is nice, then it is very likely that it is also clear. This logic also holds true the other way around – if the design is not nice, then it is most likely not clear. Another recommendation is to eliminate unnecessary indicators because a higher number of elements increases the time and reduces the clarity of the BI dashboard. Reduced clarity leads to lower appearance. A higher number of elements reduces user happiness. Also, if the designs are nice and clear, the user will be happier. The opposite is also true – if the designs are ugly and confusing, it makes the user unhappy. Ugly and confusing designs make users angry. Also, nicer designs and clearer designs make users less disgusted.

The research of the experiment was conducted during the covid-19 pandemic, and all data gathering was done through online interviews. This may lead to minor distortion between participants' results. However, despite the effort to ensure that all participants have the most similar conditions possible, it has not been possible to ensure that all participants have a high-speed internet connection and a quality webcam for the best possible emotion analysis record. Also, the environment in which the participants were located could affect the results of individual participants. Drafts of individual BI dashboards are sorted according to Table 1 and can be seen here².

Further challenges will be to replicate these results on other applications like websites, software applications or mobile apps and provide general recommendations for designing UX & UI. Further research can also lead to finding more indicators that can influence user's emotions.

² <https://github.com/Scherifow/USE-OF-EMOTION-IN-DESIGNING-BI-DASHBOARDS>

Acknowledgement

This research was sponsored by the Technical University of Liberec via the SGS project. Also, we want to thank all participants in this research for their time and help.

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