AI-based emotion recognition to study users' perception of dark patterns

Simone Avolicino[1[0000-0003-0386-5790]], Marianna Di Gregorio[1[1111-2222-3333-4444]], Marco Romano[1[1111-2222-3333-4444]], Giuliana Vitiello[1[1111-2222-3333-4444]], Fabio Palomba[1[1111-2222-3333-4444]], Monica Sebillo[1[1111-2222-3333-4444]]

[1] University of Salerno, Fisciano (SA) 08544, Italy

lncs@springer.com

Abstract. Dark Patterns are design patterns used to trick users into acting against their real interest. The web provides an infinite number of services accessible to anyone, which do not always promote a good user experience and are often structured with the aim of leading the user to perform unwanted actions or discourage him from making decisions that could damage the company. This is a very common practice, especially in neuromarketing. Human behavioral and perceptual patterns are cleverly exploited to achieve a specific goal. For this reason, dark pattern developers try to create an environment that invites as much purchase as possible by stimulating the customer's unconscious. Among the areas in which these strategies are adopted is tourism: online travel agency websites promote "fake discounts" for the products/services they are selling, display inaccurate pricing information leading to incorrect pricing assumptions, thus misleading consumers. One of the goals of this work is to identify which dark patterns are most used in online travel agencies and once identified, they will be used to run scenarios that will simulate booking a vacation online. During the execution of the tests, users will be filmed via webcam tracking their expressions and emotions through AI-based facial recognition. Finally, the data obtained from the tests will be analyzed to study the emotions and feelings that a user feels when he/she is confronted with dark patterns, to understand which users are more at risk and which are the types of dark patterns to which they are more vulnerable.

Keywords: Dark Patterns, Emotion Recognition, User Experience.

1 Introduction

User Experience (UX) Design is focused on the creation of pleasant and satisfying user experiences. It is achieved by putting the user at the center of the design process. It is a crucial component in business activities, indeed, a good UX supports growing credibility associated with the brand [24], and, consequently, the potential growth of customer loyalty during the time. Often, however, this proportional relationship is underestimated by companies, looking for short-term benefits. For example, some

online companies hide from their customers some of the costs of their services until the moment of payment. Such a strategy is commonly called "dark pattern": tricks used in websites and apps that make you do things that you didn't mean to, like buying or signing up for something [5]. However, UX is affected during all the steps of the consumer's interaction with the brand, starting from the first contact until the purchase of the product. For this reason, the main objective of UX design is not the enhancement of the product, brand, or service but the construction of a relationship as satisfying as possible for the consumer from an emotional and functional point of view.
In this work, we investigated the effects on the customer experience of the most common dark patterns. To do so, we exploited the potentiality of the AI and neural networks to monitor and extract users' emotions while interacting with an online travel agency in a controlled experiment.

2 Related works

The interface design is one of the disciplines that for several years now contributes deeply to our daily life, making fundamental digital services and products more intuitive and usable [20] [24] [25] [7]. However, there is a mischievous current of thought of who voluntarily decides to design an interface to force the user to make some actions, that most of the time benefit just the service provider. Dark patterns, so-called for the first time by UX Researcher Harry Brignull in 2010 [5], are interface elements carefully designed and combined to confuse the users, lead them to perform unwanted actions, or discourage them to make decisions that could damage the company. In addition, dark patterns may put users with disabilities at greater risk [6]. The website platform darkpatterns.org [5] presents a collection of categorized common dark patterns used in the web. It allows users to add new undiscovered dark patterns. It has a twofold function: on one hand it represents a guide for users and aims to be a tool to help them protect themselves in the "dark world" of the web; on the other hand, given the scarcity of tools for the identification of dark patterns, the public defamation of these sites could lead the owners of such applications to take steps to correct the website in order to improve the overall experience of their users.

2.1 Dark Patterns Taxonomy

The phenomenon of dark patterns was brought to light by Harry Brignull, who also provided a first and fundamental classification on the website darkpattern.org [5].
Numerous researchers, over the years, have also shown other examples of classification in articles, on personal websites, and through other media [8][9][10]. This has therefore led to an expansion of the different types of present. A further classification was presented by Gray et Al. [1], who following analysis and comparisons on the various typologies found, provided a proposal in which the patterns identified were classified within 5 macro-categories, represented in Figure 1.

These considerations arose as a result of the fact that many of the typologies concerned specific types of content (advertising, e-commerce), while others indicated more general strategies (e.g., operations to divert the user, bait and switch). These show that dark patterns are evolving as the web evolves.

	Nagging	Obstruction	Sneaking	Interface interference	Forced action
Description	Redirection of expected functionality that persists beyond one or more interactions	Making a process more difficult than it needs to be, with the intent of dissuading certain action(s).	Attempting to hide, disguise, or delay the divulging of information that is relevant to the user.	Manipulation of the use interface that privileges certain actions over others.	Requiring the user to perform a certain action to access (or continue to access certain functionality
Dark Patterns included		Price Comparison Prevention, Intermediate Currency	Forced Continuity, Hidden costs, Sneak into basket, Bait and switch.	Hidden information, Preselection, Aesthetic manipulation, Toying with emotion, False Hierarchy, Disguised Ad, Trick questions.	Social Pyramid, Privacy suckering, Gamification.

Fig. 1. Classification of dark patterns by Gray et al.

2.2 Dark Patterns in online travel agency

Online travel agencies are becoming increasingly popular in today's world. People come across one of these websites taken by the desire to travel, and they, probably, do not pay attention to the many tricks that companies use to get them where they want. Such dark patterns, which, being a little-known phenomenon, succeed to deceive the users using apparently convenient prices and availability.

The establishment of laws to counteract them led dark pattern creators to define new approaches and strategies that could circumvent them [5]. Also, the purchase and sale of products online, have significantly intensified in many fields, leading to define new patterns that could be used during any purchasing process, such as fake time offers, fake reviews to promote a product or, in general, techniques to generate in the user feelings of urgency and scarcity. Because of the scale and sophistication with which digital marketplaces and online stores may target people, market manipulation becomes even more successful [11]. Another factor to consider is that economic markets can manipulate both sellers (hosts) and buyers (travelers) [12].

In [2], the authors inspected various public domain lawsuits on online travel agencies from 2016 to 2020 to identify dark patterns in online travel agency websites. The main categories of these documents include civil lawsuits and final judgments. The dark patterns identified are “Low Stock Message”, “Activity Notification”, “High Demand Message”, “Limit Time Message”, “Hidden Cost”. In further, we explored other online travel agency websites encountering the following dark patterns in addition to the above: “Pre-selection” and “Aesthetic Manipulation”.

Each of these Dark Pattern’s tactics affects cognitive biases that can influence consumer decision making. The goal of each is to rush the user into taking a certain action, which in this case is buying a ticket.

Hidden cost.
Brignull's "Hidden Costs" pattern provides users with a late disclosure of certain costs. In this pattern, a certain price is advertised for a good or service, only to later be changed due to the addition of taxes and fees, limited time conditions, or unusually high shipping costs [1].

Activity notification.
In the "activity notification" pattern, online travel agencies' websites drag users' attention to particular product pages by indicating the online activities of other users. When online travel agencies' websites display the activities of other users, consumers are more motivated to buy the product/service [2].

High demand message, limit time message, and low stock message.
To create a sense of competition among consumers, online travel agencies use the scarcity effect as a pressure strategy to encourage purchasing. The websites of online travel agencies can use several types of dark pattern tactics to create scarcity bias. By emphasizing that the deal/sale will close soon without specifying a deadline, the limited-time message tactic creates urgency and uncertainty. The "low-stock message" indicates that the product is out of stock. Finally, the "high-demand message" tactic aims to remind users that the products/services are in high demand and will sell out quickly [2].

Pre-selection.
Any situation in which an option is selected by default prior to user interaction is referred to as a "pre-selection" pattern. "Pre-selection" is typically represented as a default choice that the product's shareholder wishes the user to make; however, this choice is frequently in the user's best interests or may have unintended consequences [1].

Aesthetic Manipulation.
"Aesthetic Manipulation" is any user interface manipulation that is more concerned with form than function. This includes design choices that draw the user's attention to one thing to redirect their attention from or persuade them to believe in something else [1].

2.3 Classification and recognition techniques of emotions

Measuring emotions has been a subject of research for many scientists, to be able to classify them and demonstrate their universality. According to the International Organization for Standardization (ISO) the user experience concept includes "Users' perceptions and responses include the users' emotions, beliefs, preferences, perceptions, comfort, behaviours, and accomplishments that occur before, during and after use" [4]. Paul Ekman [3] showed, through experimenting with people from different places, the possibility to classify emotions and demonstrated their universality. He also engaged in cataloguing human expressions, creating a coding system of facial actions (FACS). To do so, he took thousands of photos of facial expressions and associated each one with a value based on the facial muscles involved. The researcher argued that there are universal emotions that is common emotions that are the same for everyone in all cultures and can be defined as primary, such as anger, fear, sadness, happiness, surprise, and disgust, and secondary, such as amusement, contempt, contentment, embarrassment, excitement, guilt, pride, relief, pleasure, shame. For a long time, facial expression recognition and analysis, particularly FACS detection [13] and discrete emotion detection, has been a hot area in computer science, with numerous promising algorithms [14] [15] [16]. Nowadays several methods and technologies allow the recognition of human emotions, which differ in the level of intrusiveness. The use of invasive tools (e.g. ECG or EEG, biometric sensors) [17] [18] can influence the behavior of subjects and in particular can adulterate their spontaneity and, consequently, the emotions experienced by them, introducing biases that inevitably end up compromising the expected results. Most of these techniques, methods and tools refer to three areas of research: facial emotion analysis, speech recognition analysis and biofeedback emotion analysis. Facial emotion analysis aims to recognize patterns from facial expressions facial expressions and linking them to emotions. For this analysis, AI comes into play with algorithms of Deep Learning, particularly based on Convolutional Neural Networks (CNN). It is a mathematical model of Deep Learning that takes in input different types of images and makes predictions based on the trained model. CNN is not only used for emotion recognition [19] [21], but also for gestures [22][23].

3 Study on emotion recognition in relation to dark patterns

To identify the user's emotions when dealing with different types of dark models, 3 tests were conducted. The first one is to understand the technological skills and knowledge that the participants possess. The second, which is the main point of this work is divided into several tasks, one for each dark model. These tasks are about booking a ticket online, be it an airline ticket or a hotel reservation. Through this test, it will be possible to know the emotions of the users while viewing the dark patterns. The last test is used to understand the influence that these dark patterns have on purchases on websites. Moreover, it is useful to validate the data obtained from emotion recognition from test 2. The tests are conducted individually and in a specific environment.

3.1 Participants

To analyze users' emotions while viewing the dark models, users of different ages and with different technological backgrounds were chosen. Participants' age ranged from 19 to 66 (M = 35.5, SD = 14,7). Users are equally divided between participants under

35 years of age and those over 35. For this reason, in the study and analysis participants were divided into 2 categories: under 35 and over 35.

3.2 Choice of tasks

The types of dark patterns are countless, so in this work we considered all those dark patterns that can be encountered in online travel agencies (“Low Stock Message”, “Activity Notification”, “High Demand Message”, “Pre-selection”, “Limit Time Message”, “Aesthetic Manipulation”, “Hidden Cost”). We have selected some of the most famous sites that contain the presence of dark patterns, and they are listed in the Figure 2. We asked the participants to carried out come tasks on them to verify their efficiency during the booking of a travel online and to understand if they provoked particular emotions on them. The table in Figure 2 shows the websites selected for testing and their corresponding dark patterns.

	Low Stock Message	High Demand Message	Limit Time Message	Activity Notification	Hidden Cost	Pre-Selection	Aesthetic Manipulation
Booking			X				
Ryanair	X						
E-Dreams	X		X				
Expedia						X	
Volagratis							X
Mytrip							X
B-Rent					X		
Rentalcars		X		X			
Nautal		X		X			

Fig. 2. Dark patterns contained in the websites tested in this work.

3.3 Test Preparation and tool used

The test was conducted in a controlled environment and video/audio recording tools, a data collection system, etc. were set up. The study execution was conducted in person, for it we used the following tools: - DeskShare: Screen Recorder Pro[1] for recording two screens simultaneously; - Google Forms[2] for surveys; - Excel to track results; - MorphCast Emotional AI[3] for emotion recognition. MorphCast Emotional AI is a software application that uses machine learning and face recognition, as well as gender, age, and the six primary FACS emotions, to determine a user's level of attention without asking for personal information. The software is client-side (JavaScript), allowing it to avoid sending biometric data to the server. In addition, the software is browser-based, allowing it to be used simultaneously with other applications. This is an important characteristic allowing us to watch the evolution of emotions on a screen, while users working on a task using a second screen.

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1 https://www.deskshare.com
2 https://docs.google.com/forms/
3 https://www.morphcast.com/sdk/

3.4 Background survey

The background survey was used to learn about users' technological experiences and skills. The questions in this survey were: How frequently do you use smartphones, computers, tablets, etc.? How frequently do you browse the web during the day? Do you prefer to book your vacations using online services or in traditional physical agencies?

3.5 Tasks presentation and execution

Two test scenarios were identified, both of which contained websites with the same number and type of dark patterns. The first scenario includes the following tasks: - Flight booking on E-Dreams[4]; - Hotel room booking on E-Dreams; - Car rental on B-Rent[5]; - Boat rental on Nautal[6]; - Hotel room booking on Expedia[7]; - Flight booking on Volagratis[8]. The second instead: - Booking a flight on Ryanair[9]; - Booking a hotel room on Booking[10]; - Booking a car on B-Rent; - Booking a hotel room on Expedia; - Booking a car on Rentalcars[11]; - Booking a flight on MyTrip[12]. Once the instructions for conducting the test were explained, the user could choose which scenario to complete. The instructions provided indicated how to explore the websites to visualize the dark patterns and how to position oneself in front of the camera so that the recognition of the expressions would be as reliable as possible. During the execution of the various tasks, the users' emotions were analyzed by webcam through AI-based emotion recognition, as shown in Figure 3. When a dark pattern is executed, the system captures the user's expression, and the conductor records it in an excel sheet. In addition, the researchers wrote down all the comments of the participants regarding the dark patterns they met.

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[4] https://www.edreams.it
[5] https://www.b-rent.com
[6] https://www.nautal.it
[7] https://www.expedia.it
[8] https://www.volagratis.com
[9] https://www.ryanair.com
[10] https://www.booking.com
[11] https://www.rentalcars.com
[12] https://www.it.mytrip.com

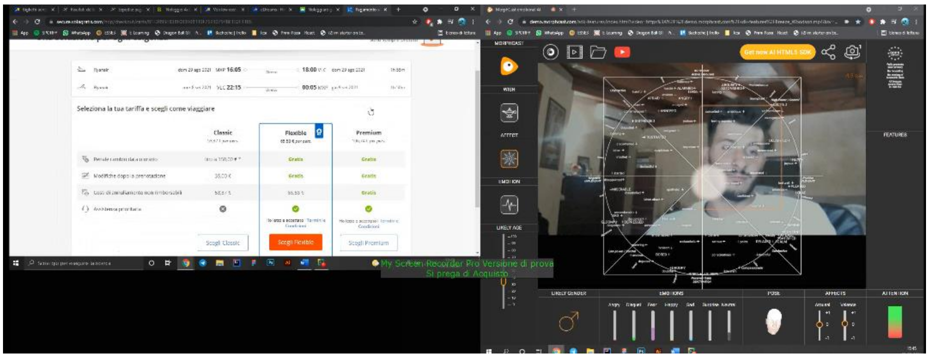

Fig. 3. A test case that shows the participant during the experiment.

3.6 User Experience questionnaire

The UX questionnaire was used to learn more about the tasks performed and was divided into 7 sections. Each section referred to a website and the dark patterns encountered. The questions for each section were 4 and were addressed to the experience had with the dark pattern displayed. The proposed questions were used to understand the influence of each dark pattern on each of the users. The questions of the survey have been: (1) Did you notice the presence of the dark pattern x? (2) Did the presence of the dark pattern influence the decision to complete the purchase? (3) Do you think that without the presence of the dark pattern you would not have completed the purchase? (4) How did you feel about the presence of the dark pattern?
Although the emotions have been analyzed by a specific software, it was useful to know the feelings that the users themselves declared to compare them with the results obtained by the software and understand whether they were related or not.

4 Analysis of results

In this section we show the results obtained through the previously mentioned surveys and those obtained through facial emotion recognition. Finally, the data obtained were compared to see their reliability.

4.1 Background survey results

From the data regarding the background survey, we found that users over the age of 35 were the participants with the poorest backgrounds. For this reason, it was chosen to divide the users in the following way: users under 35 years of age and users with an age greater than or equal to 35 years of age. This classification is useful for analyzing the data for the upcoming tests.

4.2 Emotion recognition results

This section discusses the data obtained from facial emotions recognition through MorphCast Emotional AI. Just as with the background survey, there were 50 test participants. The emotions analyzed are the primary ones cited in the above paragraph.
So, anger, fear, sadness, happiness, surprise, and disgust were measured. In addition, another emotion was added: indifference, which indicates a neutral expression that can be found when the participant does not reproduce any expression.
The graph in Figure 4 shows the emotions of all users for each dark pattern found. The Figure 5 shows the graph of emotions of all users under 35 years old for each dark pattern found. The Figure 6 instead, represents the emotions of all the users with age superior or equal to 35 years for every dark pattern found.

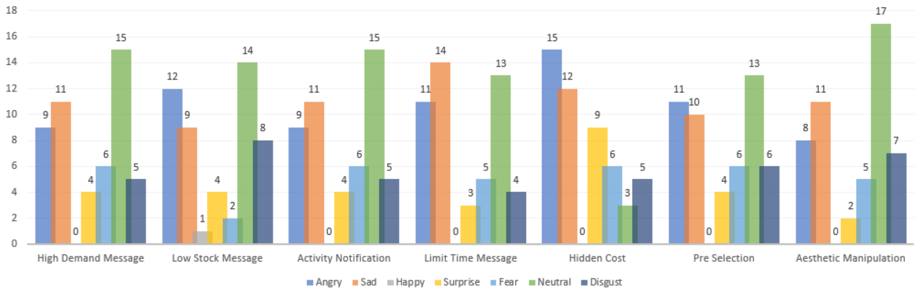

Fig. 4. Emotions of all users for each dark pattern found.

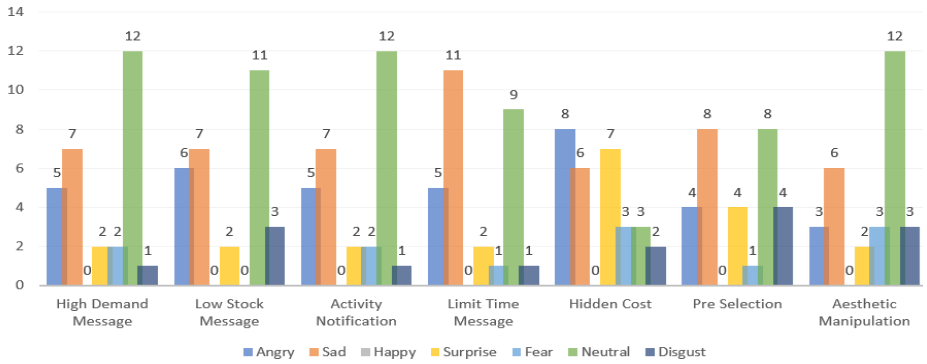

Fig. 5. Emotions of all users under 35 years old for each dark pattern found.

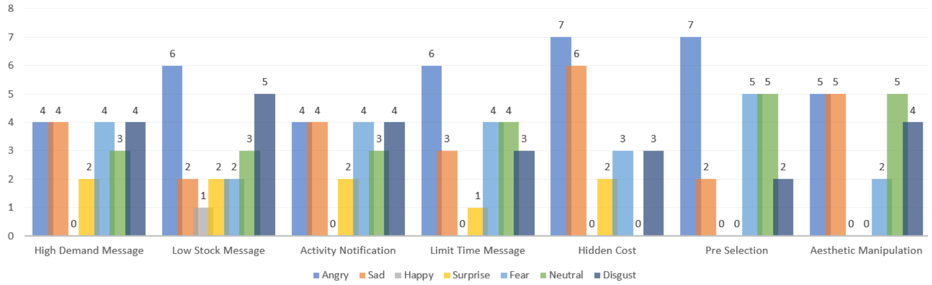

Fig. 6. Emotions of all users over 35 years old for each dark pattern found.

Table 1 reports for each dark pattern the predominant emotion resulting from the study.

Dark Pattern	Under 35	Over 35	Totality
Low Stock Message	Indifference	Angry	Indifference
High Demand Message	Indifference	Indifference, Sadness, Angry, Disgust	Indifference
Activity Notification	Indifference	Indifference, Sadness, Angry, Disgust	Indifference
Limit Time Message	Sadness	Angry	Sadness
Pre-selection	Sadness/Indifference	Angry	Indifference
Aesthetic Manipulation	Sadness	Indifference, Sadness, Angry	Indifference
Hidden Cost	Angry	Angry	Angry

Table 1. Predominant emotions for each dark pattern.

4.3 User Experience questionnaire results

The goals of the UX questionnaire are many: - To understand how many people notice the presence of dark patterns; - To understand how much the presence of dark patterns effects the choice of purchase; - To compare the data obtained from emotion recognition with the emotions obtained from the UX questionnaire to verify the reliability of the results.

Question 1.
From the data obtained from the first question ("Did you notice the dark model?") we found that all participants noticed all dark patterns, only those over 35 years old did not see the “pre-selection” pattern.

Question 2.
From the data obtained by the second question (“Did the presence of the dark pattern influence the choice to complete the purchase?”) we have discovered that only the following four dark patterns have influenced the choice to complete the purchase:

“low stock message”, “hidden cost”, “limit time message” and “aesthetic manipulation”.

Question 3.
The third question ("Do you think that without the presence of the dark pattern you would not have completed the purchase?") shows that users would have bought the product even without the presence of the dark patterns.

Question 4.
The fourth question was related to the emotion felt by the user during the vision of the dark pattern. Specifically, it was asked: "How did you feel in the presence of the dark pattern?" for each of the patterns analyzed. Table 2 shows the predominant emotion (highest percentage) regarding this question.

Dark Pattern	Under 35	Over 35	Totality
Low Stock Message	Indifference	Angry	Indifference
High Demand Message	Indifference	Indifference	Indifference
Activity Notification	Indifference	Indifference	Indifference
Limit Time Message	Sadness	Indifference	Sadness
Pre-selection	Sadness	Indifference	Sadness
Aesthetic Manipulation	Sadness	Sadness	Sadness
Hidden Cost	Angry	Angry	Angry

Table 2. Predominant emotion regarding the fourth question.

4.4 Comparison between data obtained through emotion recognition and data collected from the UX questionnaire

In this section we will compare the data obtained through the recognition of emotions and the data received from the UX questionnaire. In the previous sections are the results for each dark pattern, however it is necessary to validate these data, to understand or not if the outcomes of the different tests are correlated with each other. Also in this analysis, as in the previous ones, the users will be divided by age. The dark patterns “high demand message” and “activity notification” are shown in the same web site, therefore graphs of the dark pattern “high demand message”, that they will follow, are equal to the dark pattern “activity notification”, that will not be shown because they have given the same results. The comparison of data will follow in the following order: (1) Comparison of emotions considering the totality of users; (2) Comparison of emotions examining users under 35 years old; (3) Comparison of emotions examining users over 35 years old.

4.5 Comparison of emotions considering the totality of users

In this paragraph, the colors of the graphs indicate: - Yellow: results obtained from the UX questionnaire; - Blue: results obtained by emotion recognition.

High Demand Message and Activity Notification.
The graph in Figure 7 shows a close correlation between almost all the emotions. The expression anger did not assume the same value for both the tests, but the predominant emotions predominant for both are sadness and indifference, thus confirming the reliability of this result.

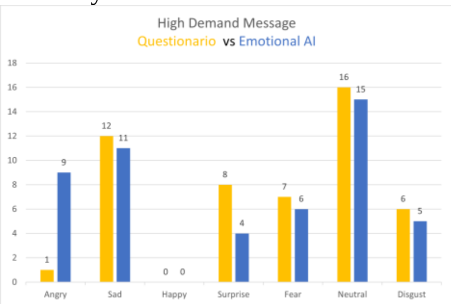

Fig. 7. Comparison of questionnaire and emotion recognition of total users' high-demand message and task notification patterns.

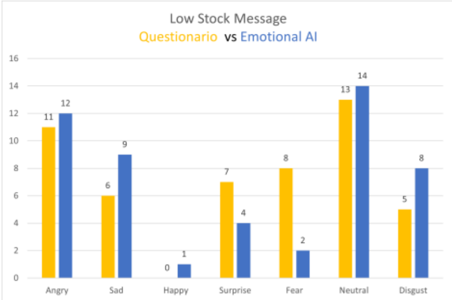

Fig. 8. Comparison of questionnaire and emotion recognition of total users' low stock message pattern.

Low Stock Message.
The comparison of the emotions coming from the dark pattern "low stock message" results coherent. In fact, the graph in figure 8 shows an almost equal relationship in the greater part of the emotions, except for fear, that assumes different values.

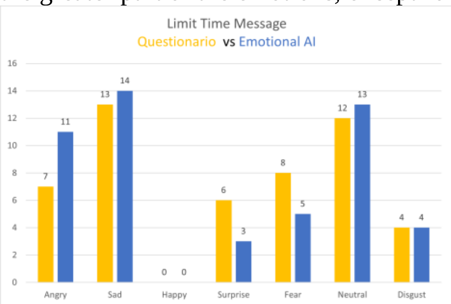

Fig. 9. Comparison of questionnaire and emotion recognition of total users' limit time message pattern.

Fig. 10. Comparison of questionnaire and emotion recognition of total users' pre-selection pattern.

Limit Time Message.
The relationship of the predominant values of the dark pattern "limit time message" is nearly equal, as we can see in the graph in Figure 9.

Pre-Selection.
For the dark pattern “Pre-selection”, the predominant emotions remain Sadness, Anger, and Indifference, even if, as we can notice from the graph in Figure 10, Sadness took on a slightly different value, although it remained among the top three.

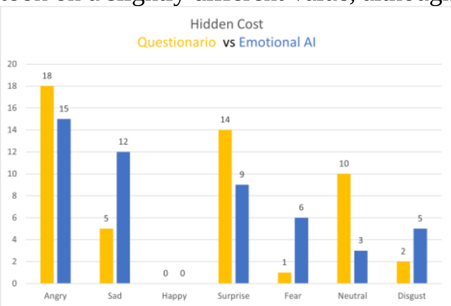

Fig. 11. Comparison of questionnaire and emotion recognition of total users' hidden cost pattern.

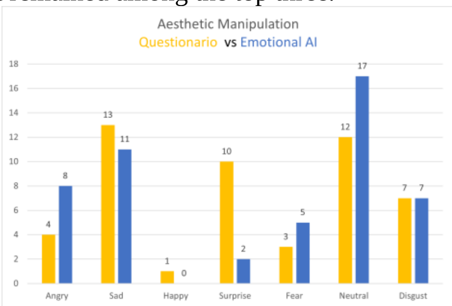

Fig. 12. Comparison of questionnaire and emotion recognition of total users' aesthetic manipulation pattern.

Hidden Cost.
From the graph illustrated in Figure 11, anger can be confirmed as the predominant emotion, however, an alteration can be seen in the emotion’s sadness and surprise. They would lead to confirm surprise as the second highest value and sadness as third.

Aesthetic Manipulation.
The graph in Figure 12 shows two primary emotions: indifference and sadness. Although the two tests provided two dominant emotions different, the values for each of them are close. We can therefore validate the results obtained.

4.6 Comparison of emotions examining users under 35 years old

In this paragraph the colors of the graphs indicate: - Blue: results obtained from the UX questionnaire; - Orange: results obtained through the recognition of emotions.

High Demand Message and Activity Notification.
What can be observed from the graph in Figure 13 is a close correlation between almost all the emotions, in particular sadness and indifference. The expression anger did not assume the same value for both tests, but the predominant emotions however, for both result to be similar, confirming therefore the reliability of such result.

Low Stock Message.

The comparison of the emotions coming from the dark pattern “low stock message” results coherent. In fact, the graph in Figure 14 shows an almost equal comparison for anger and sadness. The indifference, indicated from the voice "neutral", remains the dominant expression, despite the values of the various tests are not close between them.

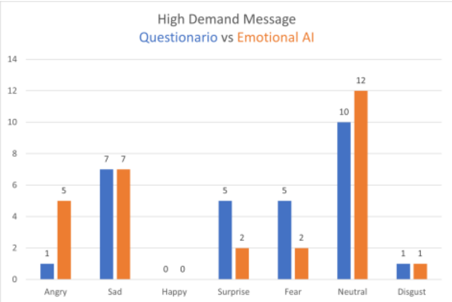

Fig. 13. Comparison of questionnaire and emotion recognition of under 35 years old users' high demand message and activity notification patterns.

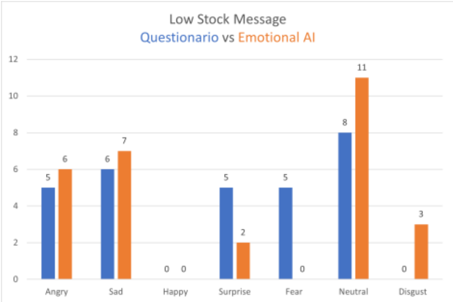

Fig. 14. Comparison of questionnaire and emotion recognition of under 35 years old users' low stock message pattern.

Limit Time Message.
The ratio of the predominant values of the dark pattern “limit time message” is fair for sadness and indifference, which are confirmed as the main emotions for this dark pattern, as we can see in the graph in Figure 15.

Pre-Selection.
For the dark pattern “Pre-selection”, the predominant emotions are sadness, anger, and indifference. Even surprise, however, as we can see from the graph in Figure 16, has reached a value like anger.

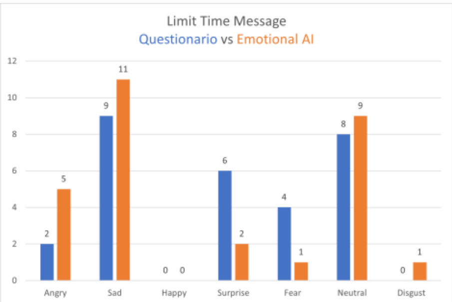

Fig. 15. Comparison of questionnaire and emotion recognition of under 35 years old users' limit time message pattern.

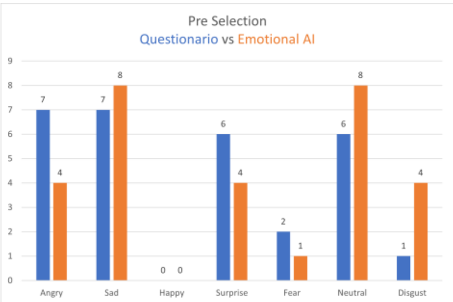

Fig. 16. Comparison of questionnaire and emotion recognition of under 35 years old users' pre-selection pattern.

Hidden Cost.
From the graph illustrated in Figure 17 we can confirm anger as the predominant emotion, followed by surprise. However, it is possible to notice an alteration of the emotions: sadness and indifference.

Aesthetic Manipulation.
The highest values concern anger and indifference, as shown in the graph in Figure 18. It can be seen that the questionnaire reported higher values for surprise.

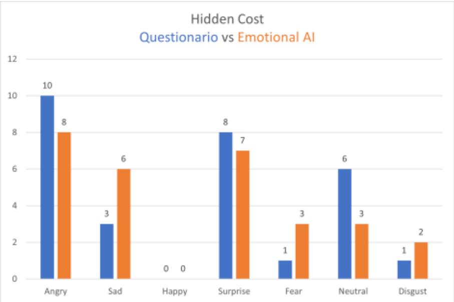

Fig. 17. Comparison of questionnaire and emotion recognition of under 35 years old users' hidden cost pattern.

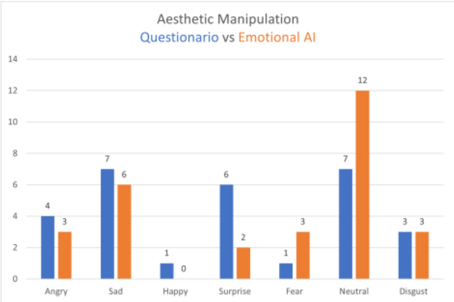

Fig. 18. Comparison of questionnaire and emotion recognition of under 35 years old users' aesthetic manipulation pattern.

4.7 Comparison of emotions by examining users aged 35 years and older

In this paragraph, the colors of the graphs indicate: - Blue: results obtained from the UX questionnaire; - Green: results obtained by emotion recognition.

High Demand Message and Activity Notification.
The values of almost all the emotions are similar, as can be seen from the graph represented in Figure 19. Disgust and sadness remain the highest values, fear instead has decreased from the results of the UX questionnaire. Same for anger, which was zero in the UX questionnaire. Indifference is also confirmed as one of the highest values.

Low Stock Message.
From the diagram in Figure 20 the same values of anger and disgust can be noticed, that represent the highest. The indifference has reached a higher value from the data of the questionnaire, but it remains however in third higher, confirming the results obtained from the test.

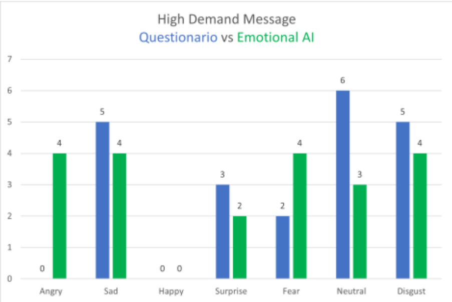

Fig. 19. Comparison of questionnaire and emotion recognition of over 35 years old users' high demand message and activity notification patterns.

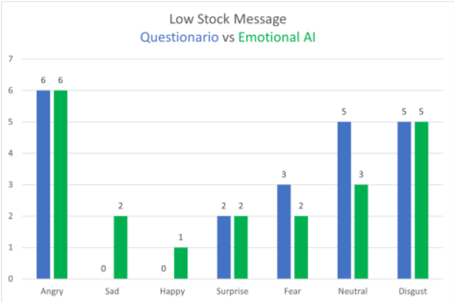

Fig. 20. Comparison of questionnaire and emotion recognition of over 35 years old users' low stock message pattern.

Limit Time Message.
The emotions detected for the dark pattern "limit time message" were the most truthful, from the graph in Figure 21 it can be observed how the values of all the emotions are tightly close.

Pre-Selection.
From the relationship illustrated by the graph in Figure 22, only two emotions can be confirmed: "indifference" and "anger". The fear and sadness found by the software for the detection of emotions was not validated by the questionnaire.

Fig. 21. Comparison of questionnaire and emotion recognition of over 35 years old users' limit time message pattern.

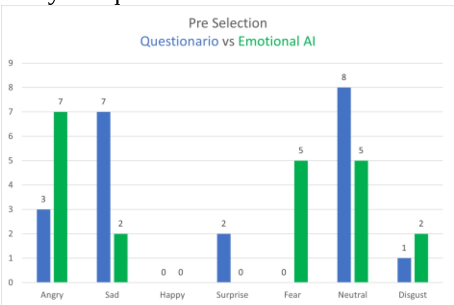

Fig. 22. Comparison of questionnaire and emotion recognition of over 35 years old users' pre-selection pattern.

Hidden Cost.
From the graph illustrated in Figure 23 we can confirm "anger" as the predominant emotion. However, the remaining values are discordant.

Aesthetic Manipulation.
The graph in Figure 24 shows the equality of the values inherent to disgust, indifference, and fear; sadness is also confirmed as the highest value. It is different instead for two other emotions, anger, and surprise.

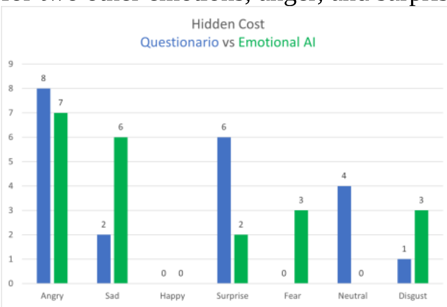

Fig. 23. Comparison of questionnaire and emotion recognition of over 35 years old users' hidden cost pattern.

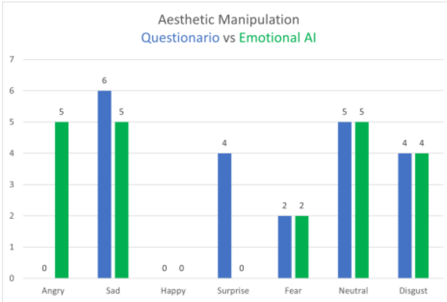

Fig. 24. Comparison of questionnaire and emotion recognition of over 35 years old users' aesthetic manipulation pattern.

4.8 Analysis

After analyzing the results, shown in the previous section, several considerations emerged.

- The under 35 represent the users with a more advanced technological background and are accustomed to such strategies and tricks, this explains the indifference for most of the dark patterns. For the patterns "limit time message" and "pre-selection" instead the perceived emotion is sadness. While anger for the dark pattern "hidden cost".
- The over 35 are more vulnerable users because they use less frequently online travel agencies to book their vacations. The emotions detected are in fact different for each dark pattern.
  - Aesthetic manipulation: sadness
  - Low stock message: anger and disgust
  - Limit time message: anger
  - Hidden cost: anger
  - Activity notification and high demand message: sadness and disgust
  - Pre-selection: indifference
- The "pre-selection" pattern has not been noticed by most users.
- The dark patterns that influence most the customer during the purchase of a product/service online are: (1) "Low stock message", (2) "Hidden cost", (3) "Aesthetic manipulation".
- The users would buy the products if they were really interested, but the dark patterns incentivize them to complete the purchases in the shortest possible time.

- The dark pattern "Hidden cost" is the one perceived with the highest values of anger probably because it is the most tangible form of deception among all the dark patterns.
- The anger, especially on users over 35, detected by facial recognition can be linked to a visual effort of the users, assuming a deep look and contracted eyebrows.

5 CONCLUSION AND FUTURE RESEARCH

In this paper, we dealt with dark patterns and the effects they cause on users. We identified the most commonly used dark patterns in online travel agencies and we investigated their effects on the customer experience by carrying out a study involving 50 participants and 9 websites. During the test, the users have been filmed via webcam in order to track their expressions and emotions through AI-based facial recognition. At the end of the task, to validate the results, we conducted a final questionnaire where all users indicated the emotion they felt during the test. The results were compared with the AI-based emotion recognition results, and we found that the over 35 are more vulnerable to dark patterns than those under 35. We realized that technological background greatly affects the emotions users may feel when interfacing with dark patterns. Not being familiar with the web makes inexperienced users easily fooled by strategies and tricks, such as dark patterns. The under 35s are more experienced users with online travel agencies and are accustomed to such dark patterns, as opposed to the over 35s, who less frequently use websites to book their vacations. Indeed, for those under 35 we have found the indifference for most of the dark patterns. For the "limit time message" and "pre-selection" patterns the manifested emotion was sadness. While anger for the "hidden cost" dark pattern. For the over 35, instead, we found different emotions for each pattern: sadness and disgust for "activity notification" and "high demand message" patterns, anger for "limit time message" and "hidden cost" patterns, for the "aesthetic manipulation" pattern the emotion was sadness and finally indifference for "pre-selection" pattern.
In the future considering that the over 35 were the ones who manifested emotions other than indifference in all dark patterns, except for "pre-selection" pattern, we plan to extend the test to other over 35 users, in order to learn more about the effects of dark patterns.

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