Human-AI Interaction – Is It Trust or Emotions That Mediates Behavioral Intensions?

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Abstract

In Human-Artificial Intelligence (AI) interaction research, trust is the dominating research domain. However, based on some recent evidence, trust feelings are not as holistic determinants as emotions in predicting eventual reactions. The objective of this research is to compare whether trust or emotions are better predictors for intentions in AI domain. Accordingly, the study adopts concepts of trust and emotions. The dual process theory offers a metalevel framework explaining some of our findings. The results imply that in contrast to the prevailing research domain and opinion, emotions play a more significant role in predicting intensions than trust. In addition, AI-generated negative images seem not to raise such emotions that would have any significant effect on intentions. Instead, AI-generated positive images created emotions that had significant effects. According to the previous literature, the negative cues emphasize the effects hence, our results challenge this view.

Keywords: AI-generated content, synthetic content, trust, emotions, dual-process theory

1. Introduction

Human-computer interaction research concerning Artificial Intelligence (AI) has exploded in the past years. Topics relate user experiences and usability [28], engagement [20], user acceptance including trust, perceived usefulness, and ease of use [40], ethics [12] and finally adoption and diffusion among different industrial and societal contexts [6].

Studies related to the emotions evoked by AI systems revolve around trust feelings. For example, trust towards AI can be enhanced if the AI system shows some emotional intelligence, transparency and explainable processing and outcomes [10].

Only a few studies introduce evoked human emotions in human-AI interaction situations. For example, study [42] results suggest that emotions might have more variation in terms of intensions than trust feelings. However, they studied only emotional trust and not any wider spectrum of emotions, which could further reveal more specific relationships with the outcomes.

The motivation for this research paper arises from recent news, indicating the flimsy use of AI images in media and communication. For example, Amnesty International was criticized for using AI-generated images [47] and the NGO had to remove their AI generated images from their campaign considering Colombia's 2021 national strikes and protests. Initially, the reason to use AI generated images (also known as synthetic content) was to protect protesters from possible state retribution. Although AI generated images were aligned with well-documented real incidences and violence carried out by the state police, it raised mistrust and conspiracy theories among the common people and furious emotions and accusations of plagiarism among the photojournalists, as in the end of the day, AI uses the existing real photos to generate new ones.

These issues of trust, emotions and reactions are not confirmatory with the existing theories about image cues. The common understanding is that while both positive and negative image cues cause corresponding emotions and intended reactions [35], the negative image cues have stronger effects [38]. There might be several explanations for this, while dual-processing theory suggests that negative cues involve besides cognitive reasoning also more affective thinking, and this interaction has stronger effects [37].

This conference paper showcases one phase of a larger research project studying a sustainability campaign by an NGO. Our between-subjects experiment considers two conditions: AI generated images that have negative and positive cues. As trust is the dominating mediator in the current AI research field, besides that, we consider emotions. Emotions are less studied in this context, but in theory, emotions could provide more holistic prediction for the eventual reactions and outcomes [42]. The results extend the current theoretical understanding about the image cue effects to consider the images generated by AI. The

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results imply the best predictors and conditions for AI generated image cue outcomes to be harnessed by AI designers and practitioners.

2.Theoretical framework and hypotheses

Figure 1 presents the theoretical framework of this study. The objective is to find out whether trust or emotions are better mediators and thus predictors of intentional outcomes. We also look at whether AI generated negative and positive image cues have any moderating effects.

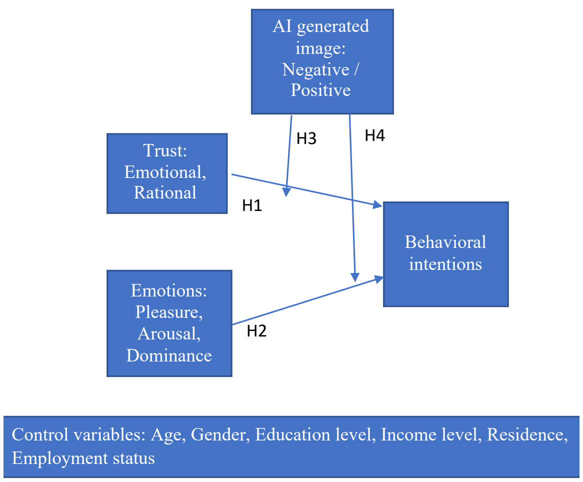

Figure 1. Theoretical framework.

2.1 AI and Trust

The essence of trust is the willingness to be vulnerable to the actions of another person [25], and trust is affected by perceptions of another person's benevolence, competence and integrity [7].

In their review, Glikson and Woolley [10] conceptualized AI trust in two main components, emotional and cognitive trust. While emotional trust can be enhanced with AI's anthropomorphism characteristics, cognitive trust is construction of AI's tangibility, transparency, reliability, task characteristics and immediacy behaviors.

Several studies support these kinds of antecedents contributing to emotional and cognitive trust. For example, a study by Hengstler and Duelli [15] shows how operational security, data security, understandable algorithms and cognitive compatibility are all interlinked in creating trust on AI systems. Similarly, high technical trustworthiness [44], explainability [1], as well as transparency and fairness [43] are all contributing to AI user trust increases.

Anthropomorphism characteristics and their positive trust effects can be enhanced with tangibility and exposure time [50], human like voice and expressions (Waytz et al. 2014) and humankind errors [25]. AI anthropomorphism including appearance can also create certain expectations, which should be met or otherwise the anthropomorphism could have negative effect on trust [2].

The AI research domain generally applies interpersonal trust and related scales as a starting point following the applications of previous technology and information system research fields (e.g., [23]). However, some opposing views exist suggesting that as AI does not possess emotional state or as it cannot be held responsible for its actions, the AI research domain should consider reliance instead of trust [39]. Nevertheless, trust increase is seen to promote general behavioral intentions as well as those in the sustainable behavior context (e.g., [19]., [45]). Therefore, we draft our first hypothesis:

H1: AI evoked trust positively affects behavioral intentions.

2.2 Emotions evoked by images

Images are emotionally powerful and can evoke a strong emotion in a viewer. For example, photographers construct images for viewer's specific emotions by using different editions and filters [33]. Houts et al [17] indicated that emotional responses to images can increase or decrease the target behaviors. Also, Vilani-Yavetz and Rafaeli [49] demonstrated that emotions are the key variable in explaining customer reactions. Emotions are predictors of behaviors and intricately linked with behavioral tendencies and "persuasion is affected by bringing an audience into a state of emotion" [17].

Valence refers to the positive or negative nature of an emotion. Mehrabian and Russell [30] and later Havlena and Holbrook [13] define three major dimensions of emotions including pleasure, arousal and dominance with different valences ranging from positive to negative. For example, in the case of pleasure, in one end there is feeling "pleased" and in the other end feeling "annoyed". Similarly, for the arousal feeling "stimulated" vs. "relaxed", and for the dominance feel of "controlling" vs. being "controlled".

Some factors that may affect these emotions include intensity [3], exposure duration [7], individuals' ability to appraise, regulate and manage their feelings [27]as well as social factors and influences [11].

Different emotions also can have different kind of effects in terms of the behavioral intensions and outcomes as reviewed by [34]. For example, happiness and enthusiasm can increase motivation, engagement, and willingness to take positive action. On the other hand, sadness and disappointment can reduce motivation and lead to withdrawal or passive behaviors. Fear and anxiety have been found to trigger avoidance behaviors or a heightened focus on self-preservation, while anger and frustration can cause assertive or aggressive behaviors aimed at overcoming obstacles or injustices.

Emotions studies have long traditions in consumer and advertising research, however, discrete emotions and their relationships with behavioral intentions and outcomes on digital platforms is still in its infancy [34]. In terms of AI-generated content, studies by Thomas and Fowler (2021) as well as Sands et al. (2022) suggest that AI influencers are perceived in similar ways as the real human influencers. Arango et al. (2023) studied AI-generated images in charity advertising and found that awareness of AI-generated images reduced the intention to donate, where empathy, anticipatory guilt and emotion perception were all significant mediators. The last one measures what kind of emotions the image represented, but not what kind of emotions it evokes among the respondents. They also found that charities adopting AI-generated images can benefit by making their ethical motives salient. Finally, consumers were found to be more acceptable towards AI-generated images in extraordinary circumstances, where predictors and outcomes were similar as in the case of real images.

H2: AI evoked emotions negatively affect behavioral intentions.

2.3 Negative and positive images cues as moderator

The common understanding is that while both positive and negative image cues cause corresponding emotions and intended reactions [35]., the negative image cues have stronger effects [38]. This effect is also hypothesized to be valid with trust.

H3: Negative image cues emphasize the effect of trust on behavioral intentions.

Negative emotions are proved to affect targeted intentions, for example, have the potential to motivate pro-environmental behaviors [26]. Similarly, Russell [38] was expecting a negative relationship between emotions and food waste behavior but it was found that positive emotions had no relationship and negative emotions clearly had a positive relationship.

H4: Negative image cues emphasize the effect of emotions on behavioral intentions.

2.4 Dual-Process Theory

Individuals tend to organize and interpret information according to their tendencies to use intuitive or analytical styles and correspondingly have different preferences and behaviors [18]. Intuitive thinkers make immediate evaluations; analytical thinkers use structural and cognitive reasoning [31].

According the dual-process theory, both trust feelings and emotions are automatic and first considered in humans' information processing, however, with unfamiliar and negative issues trust feelings fade away quickly when cognitive processing becomes dominant [48].

Emotions are significantly related to thinking styles and they provide feedback on both styles. Positive emotion led to higher intensions under emotional thinking and lower intensions under rational thinking [24]. Which thinking style is applied, is a question of context as well as individual's characteristics.

In theory, this means that emotions consider more holistically both intuitive and analytical information processing systems and as a result have better explanation power towards the eventual reactions and outcomes [9].

In this study we use dual-process theory as theoretical lenses to discuss and explain some of our findings.

3. Data and method

The study was conducted as a between-subjects experiment. A digital survey was sent with two different conditions: AI-generated negative and positive image (Figure 2). The images were generated by using Dream by Wombo AI image generator (https://dream.ai/create). For the first condition, the given prompt was to create a boreal forest with trash and a negative atmosphere. For the second condition, the prompt was to create boreal forest with positive atmosphere. In addition, a slogan "Nature loss or nature act" was added to the images – a slogan used by a nature NGO in their charity campaign. The intention was to nudge participants towards sustainable behavior by showing them images with negative and positive cues. All the participants were also informed that the images were generated by AI. Altogether 53 respondents completed the survey for the negative image condition and another group of 68 participants for the positive one.

Out of the total respondents, 52% were male. The majority of 68% were 18-34 years old, while rest of 32% were 35 years or older. Other demographic majorities included urban residency 79%, high school education 47%, personal income less than 10 000€ 45%, and occupation as students 50%.

In the survey, emotions considered three dimensions including pleasure, arousal, and dominance [13] and they were measured with 7-point Semantic Differential Scale. Trust consisted of three dimensions including benevolence, competence, and integrity [8] and it was adapted to consider technologies and information systems, i.e. rational- and emotional trust [23]. The measurement scale was 7-point Likert scale. Behavioral intentions to sustainability [4] was measured with three items and 7-point Likert scale. All these survey items are presented in Table 1 of the next section.

We run ANOVA tests, factor analysis and linear regression analysis with categorical moderator (negative / positive image) and Ordinary Least Squares (OLS) estimation method. The results of these analyses are reported in the next section.

Figure 2. AI-generated negative and positive images (Dream by Wombo).

4. Results

4.1. ANOVA

The positive picture and negative picture group did not differ significantly in terms of rational trust (F (1,119) =1.086, p=.229), emotional Trust (F (1,119) =.078, p=.781) or sustainable intention (F (1,119) =1.989, p=.161).

The positive picture and negative picture group differed significantly in terms of pleasure (F (1,119) =76.279, p=.000), arousal (F (1,119) =8.106, p=.005) and dominance (F (1,119) =5.217, p=.024).

4.2. Factor Analysis

A 26-item measurement model (Table 1) with 6 latent construct was built and tested using the data collected from the survey. The result of PCA shows that the 3-dimensioned (benevolence, competence, and integrity) trust scale (item 1-11) were integrated into 2 dimensions (rational, emotional), which is in line with the current AI research suggesting similar structures ([10] ; [39]). No item was removed from the initial model. The 26 items indicates a good fit good fit to the data with x^2/df=5.842(p<0.001).

Table 1. Factor Analysis.

Research constructs/measured items	Factor loading
Rational Trust	
The AI is competent and effective in image creation	.847
The AI performs its role of image creation very well	.865
The AI is capable and proficient in image creation	.866
In general, the AI is very knowledgeable about image creation	.826
Emotional Trust	
The AI would create images in my best benefit	.683
If I want to create images, the AI would do its best creating them for me	.611
The AI is interested in my benefits in image creation, not just its own	.806
The AI is truthful in its dealings with me	.718
I would characterize the AI as honest	.838
The AI would keep its commitments	.615
The AI is sincere and genuine	.821
Pleasure	
Happy——Unhappy	.459
Pleased——Annoyed	.917
Satisfied——Unsatisfied	.928
Contented——Melancholic	.871
Arousal	
Stimulated——Relaxed	.796
Excited.——Calm	.815
Frenzied——Sluggish	.779
Aroused——Unaroused	.499
Dominance	
Controlling——Controlled	.693
Influential——Influenced	.810
Dominan——Submissive	.801
Autonomous——Guided	.505
Sustainable Intention	
I am very concerned about the environment	.829
I would be willing to reduce or change my consumption to help protect the environment	.826
Protecting the natural environment increases my quality of life	.856

4.3. Linear Regression Analysis

In the 4-model OLS (Table 2), we accept p=.1 as significant level, which is acceptable considering a small data set we had. Different emotions ranging from pleased to unpleased, from exited to relaxed, from uncontrolled to controlled are coded from one to zero.

In model 1, the findings show that dominance is statistically significant(p=.000) and has a positive effect(β=.359) on behavioral intentions. Arousal, pleasure, emotional trust and rational are not statistically significant(p>.1).

In model 2, dominance is statistically significant(p=.000) and has a positive impact(β=.359) on behavioral intentions, other emotions, trusts, and pictures are not statistically significant(p>.1).

In model 3, pictures (p=.003), arousal*picture (p=.091), and dominance*picture (p=.078) are statistically significant. Arousal*picture(β=.687) and Dominance*picture(β=.531) have positive effect and pictures(β=-1.787) have negative effect. All the rest are not statistically significant(p>.1).

In model 4, none of the independent variables are statistically significant(p>.1). Pictures(P=.001), pleasure*picture(p=.094), arousal*picture(p=.077) and dominance*picture(p=.064) are statistically significant.

Pleasure*picture(β=.365), arousal*picture(β=.723) and dominance*picture(β=.542) have positive effect and picture(β=-1.909) have negative effect.

None of the interactions of trust and picture are statistically significant.

Interactions of emotion and picture in model 4 have positive effect on behavioral intentions. For demographical information, gender (β=.208, p=.025) and education (β=.245, p=.007) are statistically significant and have positive effects on sustainable intention.

Table 2. Ordinary Least Squares.

	Model 1		Model 2		Model 3		Model 4	
Independent variables	β	p	β	p	β	p	β	p
Rational trust	.042	.679	.041	.697	-.114	.456	-.125	.399
Emotional trust	- .064	.539	- .064	.539	-.100	.513	.002	.990
Pleasure	.118	.198	.113	.335	-.018	.899	-.095	.491
Arousal	.104	.247	.106	.253	-.151	.346	-.178	.263
Dominance	.359	.000	.359	.000	.129	.366	-.024	.865
Moderator								
Pictures			-.009	.940	-1.787	.003	-1.909	.001
Interactions								
Pleasure*picture					.282	.191	.365	.094
Arousal*picture					.687	.091	.723	.077
Dominance*picture					.531	.078	.542	.064
Rational trust*picture					.395	.209	.381	.213
Emotional trust*picture					.026	.932	-.020	.947
Control variables								
Gender							.208	.025
Age							-.029	.782
Income							-.120	.179
Habitation							.044	.636
Education							.245	.007
Employment							-.010	.923
Reliability								
R square	0.157		0.157		.288		.326	
Adjusted R square	.120		.112		.150		.215	

5. Discussion and conclusions

Our first hypothesis H1: "AI evoked trust positively affects behavioral intentions" is rejected as we did not find any significant relationship between trust and behavioral intensions in our models. Also, the second hypothesis H2: "AI evoked emotions negatively affect behavioral intentions", but due to the positive relationship between the AI evoked emotions and behavioral intentions.

While trust is the dominating research domain in Human-AI interaction research, our results suggest that emotions play a more significant role in determining eventual behavior. Also, the dual-process theory supports this finding: emotions consider more holistically both intuitive and analytical information processing systems and as a result have better explanation power towards the eventual reactions and outcomes [9]. The finding is also in line with Shi [42] suggesting that emotions might have more variation in terms of intensions than trust feelings. Also, Ryan [39] was skeptical on applying trust in AI research, as AI does not possess emotional state or as it cannot be held responsible for its actions. Therefore, his suggestion was to consider reliance instead of trust [39]. On the other hand, Glikson and Woolley [10] conceptualized AI trust in two main components including emotional and cognitive trust, but this concept waits for a proper scale development for the AI domain.

Our results also rejected the hypothesis H3: "Negative image cues emphasize the effect of trust on behavioral intentions". This is aligned with the dual-process theory, suggesting that with negative issues trust feelings fade away quickly while cognitive processing becomes dominant [48].

In addition, our findings rejected the hypothesis H4: "Negative image cues emphasize the effect of emotions on behavioral intentions", as the result was opposite: positive image cues emphasize the effect of emotions on behavioral intentions. This finding underscores the peculiar role of AI and challenges the existing view that the negative cues emphasize the effects [38].

Part of the existing research suggests that AI-generated content has similar effects than human made content (Thomas and Fowler 2021; Sands et al. 2022). However, Arango et al. (2023) found decrease in empathy and further in anticipatory guilt, emotion perception and intentions. Also, our findings support the view that AI-generated content results in different perceptions and outcomes compared to the conventional models and theories and hence they should be applied with caution.

5.1 Limitations and future research

There are unlimited number of various image features as well as enabled human-image interactions that have effect on human trust, emotions and intentions, but this study at hand is limited to compare only the effects of AI generated negative and positive image cues.

The absence of AI specific scale on trust / reliance can be considered as one limitation in our study and results. It is recommended that future studies could develop a proper scale for the AI domain considering emotional and cognitive trust dimensions and all their components including anthropomorphism characteristics, tangibility, transparency, reliability, task characteristics and immediacy behaviors as suggested by Glikson and Woolley [10].

There are also some factors that may affect emotions hence they should be controlled in future research. These factors include intensity [3] exposure duration [7] individuals' ability to appraise, regulate and manage their feelings [27] as well as social factors and influences [11].

Also, the fact that different emotions can have different kinds of effects and outcomes should be considered in different experimental settings. For example, some settings could consider happiness and enthusiasm and their effects on motivation, engagement, and willingness to take positive action.

Other settings could involve sadness and disappointment, where motivation and withdrawals or passive behaviors could be measured. Fear and anxiety settings could be created to test avoidance behaviors and self-preservation. Finally, the role of anger and frustration mediating the outcomes of overcoming obstacles or injustices is another setting, where AI-generated content research could make contributions and reshape the existing theories.

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