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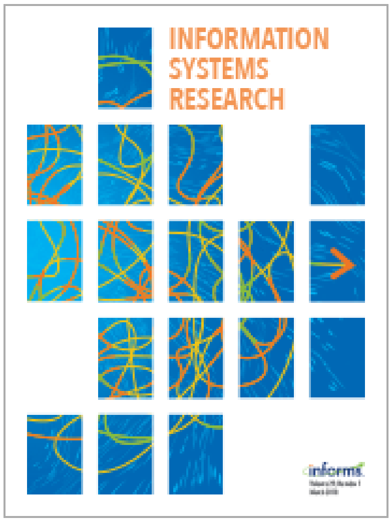

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Threatened by AI: Analyzing Users' Responses to the Introduction of AI in a Crowd-Sourcing Platform

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Abstract. As artificial intelligence (AI) solutions are being rapidly deployed, they increasingly compete with human labor. This study examines designers' strategies in response to the threat from the introduction of an AI system for simple logo designs in a crowdsourcing design platform. We study designers who were active both before and after the introduction of the AI system to understand their responses to the threat from AI. Our study is informed by the theories of threat, specifically the protection motivation theory that posits that individuals will respond to threats based on their capabilities. We find that, although some designers who had primarily participated in contests for lower-tier, simple logo designs leave the platform, others continue to participate in these contests. Interestingly, designers who have higher capabilities, evidenced by their prior participation in more-complex higher-tier logo-design contests and contests in other nonlogo categories, move away from the primary locus of threat in the lower-tier and switch to the more-complex contests after the introduction of the AI system. More interestingly, we find that successful designers respond differently from unsuccessful designers on the platform. Although unsuccessful designers increase participation across multiple contests, they do not change the quality (emotional content and complexity) of their design submissions after the AI launch. In contrast, successful designers become more focused (i.e., they substantially increase the number of submissions within a contest) and more quality oriented (i.e., they increase emotional content and complexity of their design submissions) after the AI launch. These findings have important implications for the nascent research on the impacts of AI on users in a crowdsourcing platform and for the design of such platforms.

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Keywords: artificial intelligence • crowdsourcing • users' strategies • image analytics • PMT • threat of AI

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1. Introduction

With the rapid deployment of new machine learning and artificial intelligence (AI) solutions, these systems increasingly compete with human employees (Frey and Osborne 2017). Over the centuries, a plethora of technologies have enabled the automation of routine tasks. These technologies, from steam engines to industrial machinery, have proven superior to humans on a variety of dimensions such as *power*, *speed*, *productivity*, *quality*, *accuracy*, *reliability*, *durability*, and often, in *cost* (Autor 2015, Chui et al. 2016). Given the superiority of these technologies in their specific tasks, they have quickly replaced humans that have traditionally performed those tasks and human workers have had to quit and switch to other "less automatable" tasks (Dixon et al. 2019). Interestingly, AI systems go beyond just automation of routine tasks as they can "learn" from past data to provide novel solutions. Increasingly, such AI systems are being deployed for creative tasks, which have largely been the domain of humans. In the case of creative tasks, faced with the threat of competition from AI, humans can either quit those tasks that the AI systems perform or can compete by leveraging such qualities as imagination, creativity, and emotional expression (Hertzmann 2018, Lu et al. 2020). There is very little systematic understanding of users' behaviors and strategies in response to the introduction of AI systems. In addition, studies examining the impacts of adoption of AI have largely focused on their adoption at the level of industries, geographic regions, or within firms (Acemoglu and Restrepo 2017, Graetz and Michaels 2018, Dixon et al. 2019). However, there are hardly any studies that examine the introduction of AI in decentralized marketplaces or studies that examine how individuals respond to the adoption of AI systems for creative tasks.

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This study seeks to fill this gap by studying a crowdsourcing platform for design tasks that has introduced an AI system for logo design (AI logo maker) that can compete for design tasks with human designers on the same platform. Access to large-scale granular data on designers' behaviors before and after the AI system launch provides us an opportunity to study designers' heterogenous responses to this exogenous change. In this study we seek to answer the following research questions:

How do designers respond to the introduction of the AI system for logo design tasks?

How do the behaviors of successful designers differ from the behaviors of other designers in response to the introduction of the AI system?

This study builds on the theory of threat. Specifically, we use a theoretical lens of the protection motivation theory (PMT; Rogers 1975, 1983) to understand possible responses of designers to the threat of AI. The protection motivation and protection behaviors depend on whether individuals feel the threat and whether they have coping abilities to deal with the threat. According to the PMT, individuals who do not perceive a threat will not respond to it. Among the others, individuals will take steps to avoid the threat or exhibit adaptive behaviors based on their ability to deal with the threat.

We study a crowdsourcing platform for design tasks that introduced an AI system for simple logo designs at the beginning of April 2018. Before the AI system introduction, clients would run contests with human designers on the platform. After the AI system introduction, clients have an option to run contests with human designers or use the AI system for logo design. We collect comprehensive data on all design contests with human designers for the periods of six months before the AI launch and six months after the AI launch. The data set includes 5,737 contests and the complete history of participation for 9,280 designers, which includes a total of 425,475 design submissions. We track contestants who were available in both periods and compare the behaviors of designers to understand their responses to the introduction of the AI system. To understand whether and how designers change their design submissions in response to the threat from AI, we measure the designs' emotional content and complexity because those variables have been shown (by prior research in psychology and marketing) to affect esthetic perception of art and design images as described later. We then examine whether and how the emotional content and complexity of design submissions affect the likelihood of winning a contest and how these differ for successful and unsuccessful designers before and after the introduction of the AI system.

In the context of our study, as predicted by the PMT, designers who have historically participated only in nonlogo contests will not feel the threat from the AI system that generates simple logo designs, and hence, will not respond to the introduction of the AI system. This group of designers serves as the control group in our study. Our identification strategy involves a "before-after" analysis for the same set of designers active on the platform both before and after the AI introduction. To support a causal identification of the effects, we also use propensity score matching techniques (PSM) and a difference-in-differences (DiD) method (Smith and Todd 2005) to compare the effects in the treatment groups (i.e., users affected by the introduction of the AI logo maker) with the effects in the control group (i.e., users participating in other nonlogo contests both before and after the introduction of the AI logo maker). As a robustness check, we also use logo designers in a second platform, i.e., a crowdsourcing platform where there is no AI system, as a second control group and find the results to be consistent.

In previewing the results, we find that the AI system cannibalizes lower-tier less-complex logo-design contests that have a lower award amount (lower than the median award value of 110 USD), whereas it has no significant impact on the number of available contests in the higher-tier or in other (nonlogo) design categories. In keeping with the predictions of the PMT, we find that designers respond differently to the threat from AI based on their abilities. We find that designers who have the lowest capabilities as measured by the emotional content and complexity of their design submissions (before the AI launch) are more likely to avoid the threat of AI by leaving the platform. Among others, we find that designers who had prior exposure to higher-tier logo contests involving designs with higher level of complexity and emotions are more likely to move away from the locus of the threat and to higher-tier logo contests after the AI launch. Similarly, we find that designers who had prior exposure to nonlogo design contests are more likely to move away from logo design contests to nonlogo design contests characterized by the highest complexity and emotions in design submissions on the platform.

Perhaps, the most interesting set of results pertain to the differences in how successful designers respond to the threat from AI compared with unsuccessful designers. In examining how the behaviors of successful designers and the others differ in response to the AI system launch, we find that in contrast to the unsuccessful contestants who increase the number of contests they participate in (by 13%–15%), the successful contestants substantially increase the number of submissions (by 30%–60%) within a contest compared with the period before the AI system launch. Furthermore, we find that with an increase in the number of submissions by successful designers, there is a concomitant significant increase in the emotional content and the complexity of their designs after the AI system launch. On the other

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hand, there is no significant change in the emotional content or complexity of the design submissions by the unsuccessful contestants when comparing the periods before and after the AI system launch.

These findings show that the successful contestants behave in line with well-established research on the key factors that drive esthetic experience in design. Seminal work in the psychology of esthetic experience by Berlyne (1974) finds that two interrelated constructs affect human esthetic experience: complexity and emotions. More recent research (Marin et al. 2016) finds that complexity and emotions are positively associated in creating an esthetic experience and that complexity is positively associated with beauty. The focus on improving emotional content and complexity of design submissions by winners is also meaningful considering the current limitations of AI systems. Research on the limitations of AI shows that humans are better than AI systems when it comes to qualities such as creativity, imagination, and emotions in general (Braga and Logan 2017) and more so in the case of applications in design and art specifically (Hertzmann 2018, Mazzone and Elgammal 2019).

Our empirical analyses exclude other competing alternative explanations such as changes in competition, changes in clients' feedback patterns, and changes in contests' tasks requirements that happen after the AI system launch. As an additional robustness check, we also survey designers on Amazon Mechanical Turk. Specifically, we find that the vast majority of designers indeed recognize the threat of AI for logo design. Furthermore, we find that the more-experienced designers in our survey are more likely to deal with the threat of AI by improving the quality of their logo designs, whereas the less-experienced designers are more likely to avoid the threat of AI by leaving the platform. It is also pertinent to note that, in keeping with our empirical findings, some of the designers responding to the open-ended question in our survey indicate that they will increase complexity and will add emotional content to designs.

The findings of this study have important theoretical implications. First, our findings contribute to research using theories of threat by examining a new context of the threat of AI on a crowdsourcing platform. To the best of our knowledge, this paper is among the first to show the heterogenous responses to the threat of AI in a large-scale empirical setting. Existing research (Wolbring and Yumakulov 2014, Li et al. 2019) that explores the responses of employees to the "threat" of AI systems, has been mostly conducted using surveys of employees, and the findings have been context specific. This study is among the first to use granular and longitudinal data to examine users' responses to the introduction of an AI system and by doing so contributes to this nascent stream of empirical research in this area. Our findings also highlight the differences in individuals' responses to the threat of competition from AI as compared with prior technologies which have essentially replaced humans performing those tasks. Next, the findings of this study contribute to the nascent research stream related to employment effects of AI (Dixon et al. 2019) and employees' reactions to competing AI systems (Lu et al. 2020). Prior research on the effects of AI on employees has been mostly conducted at the industry level and at the firm level (Acemoglu and Restrepo 2017, Dixon et al. 2019). This stream of research finds that overall effects of AI are negative at the industry level, but positive at the firm level for most workers except for managers who are more likely to be displaced by AI systems. Our study is among the first to extend this line of research to a decentralized crowdsourcing platform where participants are free to choose how they respond to an exogenous shock on the platform. This study goes further to shed light on how successful designers are different from the others in how they respond to the introduction of the AI system on the platform and contributes to the emerging research that seeks to understand the effects of AI systems in business setting.

Prior work in psychology (Berlyne 1974, Marin et al. 2016) and marketing (Pieters et al. 2010, van Grinsven and Das 2016, De Marchis et al. 2018) has identified the role of emotions and complexity in driving the esthetic perception of design in general and the logo design in particular. Our study is among the first to leverage large-scale granular data and state-of-the-art image analytics techniques to empirically test these theories in an online crowdsourcing platform for design tasks.

The findings of this study also have important practical implications. Platform providers can use our findings to better evaluate the impacts of AI systems on contests and designers' behaviors. Understanding how different groups of users respond to the launch of an AI system can help market providers to design relevant pricing and marketing strategies to optimize performance and revenue from both sources: AI and human designers. A more nuanced understanding of the capabilities and limitations of AI systems relative to those of expert human designers can help platform providers recommend specific guidelines for contest holders and contest participants to improve outcomes. This could also pave the way for hybrid solutions that leverage the capabilities of both the AI system and human experts.

2. Related Research and Theoretical Underpinnings

2.1. Impacts of AI on Organizations

Recent research investigates the effects of adoption of AI on employment and skill composition (Acemoglu and Restrepo 2017, Graetz and Michaels 2018, Mann and Püttmann 2018, Dixon et al. 2019). Although some of this research examines the impacts of AI at the industry and

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geographic region levels, more recent research studies relevant outcomes at the firm level. At the industry level, the effects of AI on employment are mostly negative, whereas at the firm level, they are more nuanced. For example, Dixon et al. (2019) find that, at the firm level, the employment effects of AI adoption are positive. The authors also find that, surprisingly, the adoption of AI is associated with the displacement of managers.

This study continues the previous stream of research and seeks to understand how AI systems impact design contests and individual designers on a crowdsourcing platform where the participants are freelancers. Thus, in contrast to prior work, this study seeks to investigate the impact of the adoption of the AI system on the users' behaviors and strategies on such platforms where participants are free to leave the platform at any time or switch to other available jobs on the platform.

Another related stream of research examines employees' responses to the adoption of AI, including their perceptions concerning job security and pressures to enhance skills and competences (Lu et al. 2020). These studies use surveys to document the effects of the "threat of AI." This stream of research finds that the responses of employees to AI adoption might be context specific. For instance, Wolbring and Yumakulov (2014) study the perceptions of smart AI robots by workers in disability care and find that workers do not feel threatened as they believe that these AI robots cannot replace human interaction or emotional companionship. In contrast, Li et al. (2019) find that in the hospitality industry, hotel employees are more likely to quit if they are aware of the implementation of AI and robotic platforms.

Our study extends this line of research and seeks to understand designers' responses to the "threat of the AI system" in a decentralized crowdsourcing platform for design tasks. What differentiates this research setting from prior research is that we can observe designers' abilities and their choices in response to the introduction of the AI system. More importantly, given the decentralized nature of the platform and the diversity of participants, our study focuses on understanding how heterogenous users respond to the introduction of an AI system that is a direct potential competitor for design tasks on the platform.

2.2. AI Systems and Prior Technologies

Prior studies (Brynjolfsson and McAfee 2014, Makridakis 2017) have identified three distinct periods of technological evolution, beginning with the "industrial revolution" characterized by the domination of mechanical technologies ranging from steam engines to cars. These technologies that were superior in power and speed were primarily used for substituting *routine manual* tasks such as rowing, lifting objects or moving/walking, and so on. This period was followed by the "digital revolution," which started with the invention of the computer in 1946 and continues with the widespread usage of personal computers, smart phones, and networked devices. These digital technologies have proven superior to humans in *productivity, quality, accuracy, reliability, durability,* and often in *cost* and have rapidly substituted humans in the performance of *standardized mental tasks* (Brynjolfsson and McAfee 2014, Autor 2015, Chui et al. 2016). The ongoing "AI revolution," starting with neural net devices in the 1990s, and the development of more recent applications of computer vision and speech recognition, is characterized by technologies that seek to mimic human brain power and cognitive abilities (Wang and Siau 2019) and could potentially perform all *mental* tasks (Makridakis 2017) including creative tasks such as design and art generation. Specifically, AI technologies are seen as distinctly different from prior generations of technologies in that they can learn and update using data such as numeric data, as well as text, audio, and video (Huang et al. 2019). These AI systems increasingly perform or simulate nonroutine tasks requiring "tacit" knowledge by learning from prior successful examples of those tasks and using a process of exposure, training, and reinforcement (Autor 2015). These differences between AI and prior technologies point to the differences in how humans can respond to the introduction of prior technologies and to the introduction of AI systems. Because prior generations of technologies are superior to humans in routine manual and standardized mental tasks, humans have found it increasingly difficult to compete with these technologies due to lack of superior capabilities and have been replaced by these technologies for those tasks and have had to switch to other jobs/tasks (Brynjolfsson and McAfee 2014, Autor 2015, Acemoglu and Restrepo 2018). In contrast, when AI systems are introduced, especially in creative tasks, humans have an option to quit, but they can also compete with AI systems by leveraging their creativity, intuition, imagination, and emotional expression (Brynjolfsson and McAfee 2012, Hertzmann 2018, Huang et al. 2019, Lu et al. 2020). Our study contributes to this research stream by examining how different human designers respond to the introduction of the AI system for design tasks.

Prior research on AI limitations indicates that, although modern AI systems with advanced deep learning capabilities are very impressive, humans are still more advanced in such qualities as creativity, imagination, and emotions in general (Braga and Logan 2017) and creativity and emotional and social intentions in design and art specifically (Hertzmann 2018, Mazzone and Elgammal 2019). Recent advances in generative adversarial networks (i.e., so-called creative adversarial networks) suggest that algorithms can be trained to use the same distribution of styles used by human artists but at the same time to maximize the differences between a new algorithmically generated art and all prior works, thus making the AI-generated art as novel as possible

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(Elgammal et al. 2017). However, there are profound differences between machine "creativity" and human creativity. Mazzone and Elgammal (2019) highlight that a machine uses a combination of given elements as training sets without an outside reference, whereas a human artist gets inspiration from something in the outside world (e.g., nature). Additionally, Hertzmann (2018) argues that an important role of the artist is to supply the "intent" and the "idea" for the work. Hertzmann (2018) also notes that human artists possess creativity, growth, and responsiveness and to achieve human level of art creation an AI machine needs to have capacity for consciousness, emotions, and social relationships.

Despite the current limitations of AI systems for design, they are increasingly being deployed by a variety of platforms for creative tasks. This study contributes to this stream of research on AI capabilities and limitations by focusing on the specific AI system for logo design. Although the primary goal of our study is to shed light on how human designers respond to the introduction of an AI system for logo design, we also seek to understand how the logos designed by human designers are different from AI-generated logos. Understanding the differences between AI-generated logos and human logos will also shed light on specific skills that human designers need to develop to successfully respond to the introduction of AI systems.

2.3. Contestants' Behaviors and Strategies on Crowdsourcing Platforms

This study also builds on prior research that examines strategies and behaviors of contest participants in crowdsourcing platforms. Prior research focuses on the behaviors and strategies of contest participants relating to responses to different project types and task specifications (Chen et al. 2014), to the choice of contests to participate in, and to the number of submissions within a contest (DiPalantino et al. 2011, Bockstedt et al. 2016). For example, Chen et al. (2014) find that more-complex tasks typically attract fewer contestants. In examining contestants' preferences for contests to participate in, DiPalantino et al. (2011) find that contestants choose contests depending on specific award ranges that correspond to their skill level, whereas Bockstedt et al. (2016) find that the number of submissions has a curvilinear relationship with the probability of a success in a contest. This study adds to this stream of research by examining whether and how designers change their behaviors after the AI launch.

A second related stream of research in this domain focuses on the differences in behaviors between successful contest participants and others and finds that successful contest participants are typically more experienced (Khasraghi and Aghaie 2014), and they are strategic about timing their submissions (Yang et al. 2010). Yang et al. (2010) find that successful contest participants prefer submitting at the beginning or at the end of a contest, whereas Archak (2010) finds that successful top contest participants might enter contests earlier to "deter" entries from other participants.

This study continues this stream of research and seeks to understand strategies and behaviors of successful contest participants as a response to the introduction of the AI system, as well as whether, and how, they differ from the responses of other contest participants. Focusing on the responses of successful designers will also help us understand what it takes to be successful for humans against the "threat" of AI.

2.4. Theoretical Underpinnings

To understand possible responses of designers to the threat of AI, we use the theoretical lens of the PMT (Rogers 1975; 1983, Norman et al. 2015). This theory, developed from communication and persuasion theories in psychology (Hovland et al. 1953), has been widely used in health communication research (Norman et al. 2015). In business research setting, this theory has been used in the marketing research to study advertising message themes (Pechmann et al. 2003) and in information systems research to understand the responses to IT threats (Johnston and Warkentin 2010) and adoption of secure behavior (Steinbart et al. 2016). According to PMT, a person first experiences two responses to a threat: threat appraisal and coping appraisal. During the threat appraisal process, an individual evaluates severity of the threat and vulnerability to the threat. During the coping appraisal process that happens in parallel to the threat appraisal, a person evaluates their ability to cope with the threat, response efficacy, and response costs (Rogers 1975, 1983). As Rogers (1983, p. 169) notes, "not only must the coping response be effective, but one must possess the ability to make that coping response."[1] A meta-analysis of the main constructs of the PMT has found that the ability to cope with the threat (self-efficacy) is the strongest predictor of protection motivation and behavior (Norman et al. 2015). In summary, PMT predicts that individuals' responses to a threat depends on whether they perceive the threat and, on their ability to cope with it. Abilities to cope with the threat are evaluated against the costs and response efficacy (i.e., effectiveness of the strategy to respond). Individuals who do not perceive the threat do not respond to it and hence, are the least likely to change their behaviors. When individuals perceive the threat as high but do not have an ability to adequately cope with the threat (which means that their abilities are lower than the costs of directly dealing with the threat in their chosen response strategy), they are more likely to avoid the threat rather than undertake activities that directly deal with the threat (Rippetoe and Rogers 1987). When individuals perceive the threat as high and they possess the ability to cope with the threat (i.e., their abilities are higher than the costs of directly dealing with the threat in their chosen response strategy), they are

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more likely to adapt their behaviors to directly deal with the threat.

There are several ways designers can respond to the threat of AI. In line with the predictions of the PMT theory, we expect that designers who are not directly threatened by the AI system for logo design, such as those participating in nonlogo design contests, will not change their behaviors and will continue to participate in nonlogo design contests. In contrast, we expect that designers participating in logo design contests for whom the threat from the AI system for logo design is high, will respond to the introduction of the AI system. Of these, as predicted by the theory, the designers with the lowest coping abilities, that is, those participating primarily in lower-tier logo design contests that call for simple design solutions (i.e., contests with lower costs of participation), will avoid the threat of AI by leaving the platform. On the other hand, we expect that the designers with higher coping abilities, that is, cross-tier and cross-category designers who have made design submissions before the AI introduction to higher-tier logo design contests or to nonlogo contests that entail more-complex design solutions (i.e., contests with higher costs of participation) will respond to the threat from AI by moving away from the locus of the threat, that is, by switching to those higher-tier logo design contests or to nonlogo contests after the AI introduction.

Even within these different tiers (lower-tier and higher-tier logo contests), we would expect successful designers (who have higher abilities) to respond differently to the threat from AI as compared with the unsuccessful designers. To determine the direct response to the threat of AI, we first evaluate what elements of logos could be improved to differentiate human logos from AI-generated logos. Berlyne's psychobiological model of esthetic experience in art perception (Berlyne 1974, Marin et al. 2016) provides valuable insights into how these successful designers might respond to the perceived threat from the AI system. Specifically, Berlyne's model proposes two interrelated constructs that affect human esthetic experience in art: complexity and emotions (specifically, arousal or excitement). More recent research that uses Berlyne's model (Marin et al. 2016) finds that complexity and arousal are positively associated in all conditions. The authors (Marin et al. 2016) also find that complexity is positively associated with beauty. More recent research in marketing finds that higher design complexity of an ad image helps increase attention to both the pictorial and the advertisement as a whole, positively affects ad comprehensibility, and attitude toward the ad (Pieters et al. 2010). More specific to logo design, van Grinsven and Das (2016) find that logo complexity positively affects long-term brand recognition and brand attitude in the case of repeated exposures. Researchers (Salgado-Montejo et al. 2014, Bajaj and Bond 2018) also find that positive emotions expressed in logos have positive effects on the attitude toward brands (De Marchis et al. 2018). De Marchis et al. (2018) find that excitement and happiness are strongly associated with logo esthetic attraction. Additionally, prior research finds that there is positive correlation between subjective human-rated logo complexity and logo "emotionality" (De Marchis et al. 2018) and positive relationship between logo complexity and excitement (Bajaj and Bond 2018). Thus, Berlyne's model of esthetic experience in combination with PMT predicts that successful logo designers would differ in their response to the threat from AI compared with the unsuccessful designers. Specifically, we expect that successful designers who have the ability to improve the quality dimensions of logos such as emotional expression and complexity will directly respond to the threat of AI by differentiating their designs from the AI system through these esthetics dimensions. In contrast, we expect that unsuccessful designers who are less able to improve the quality (emotional expression and complexity) of their designs will choose to compete by increasing the quantity, rather than quality, of their submissions in response to the threat of AI.

Our study builds on these theoretical underpinnings and seeks to understand whether successful contest participants are better able to leverage those attributes in response to the introduction of the AI system compared with other designers in logo design contests on the platform.

3. Research Context, Data, and Measures

The crowdsourcing platform we study allows clients to create design contests and allows designers to submit solutions for a monetary award. Logo design contests constitute the main category of contests (90% of contests), whereas other categories (10%) include nonlogo design contests mostly for design of T-shirts. The basic lower-tier logo contests have an award amount below the median value of 110 US dollars and seek simple design solutions. Clients with more-complex requirements typically choose a higher award amount (from 110 US dollars up to 2,284 US dollars; Table 1). Interestingly, at the beginning of April 2018, the focal platform introduced an AI logo maker that offers hundreds of logo designs based on a client's inputs such as a company name, a slogan, preferred styles, colors, and shapes. The whole process of logo generation using the AI system takes about five minutes. Once a client has made a choice, he or she can purchase the logo created by the AI system and acquire all the rights to use the logo. The basic price of an AI-generated logo is 20 US dollars, whereas the full resolution logo with different formats costs 65 US dollars. This pricing is close to the pricing of lower-tier contests where clients with simple requirements can invite solutions from designers. The whole process for a contest with human designers may

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take up to 10 days to complete. There are advantages and disadvantages of using human designers versus using the AI logo maker. On the one hand, the AI logo maker is very fast, and as described by its creators, it constantly learns as more people use it and it follows the most recent trends in logo design. On the other hand, a contest with human designers might provide more suitable logos with potentially better quality from professional designers. Before the introduction of the AI logo maker, clients would visit the platform and run contests with human designers. But after the AI launch, clients have a choice to either use the AI system or run a contest with human designers. This setting provides a unique opportunity to understand the impact of the AI system on individual users' behaviors and strategies in response to the AI system. It is pertinent to note that the introduction of the AI logo maker is public knowledge for both clients and designers on the platform. Prior to the AI system launch, there is no mention of it on the website, whereas after the AI system launch, the main web page on the platform's website was updated to showcase the new AI system.[2]

We collect data for the period of six months before the launch of the AI logo system (from October 2017 until March 2018) and six months after the AI system launch (from April 2018 to September 2018). As noted earlier, the AI system was launched at the beginning of April 2018. The data set includes all 5,737 contests for logo design and other types of design contests for that period and the complete history of participation for 9,280 designers, which includes a total of 425,475 design submissions (Table 1).

To initiate a contest, a contest holder needs to provide an award amount, a task description that includes a name to use in a logo, description of target audience, organization or a product, and any specific requirements. During a contest, designers submit their designs (and all designers can resubmit their designs), and a contest holder provides star ratings to select submissions. Because most contests (98.3%) are "hidden," designers can only see others' profiles (and experience), order of submissions, and star ratings, but not the submissions themselves. At the end of a contest, a contest holder announces a winning submission. Apart from the variables in Table 1, we measure the following variables related to contests and designs: contests' task descriptions' requirements, complexity, and emotional content of design submissions. Additionally, other important variables that we define include the classification of designers participating in different contests (logo and nonlogo contests) and successful and unsuccessful designers.

3.1. Task Descriptions' Requirements Classification

To begin with, we manually classify task requirements in 300 random contest descriptions. The main categories that we observe are as follows: *concrete or specific requirements*, such as "I want the picture of a child with the graduation cap as the shadow"; *abstract requirements*, such as "Overall design must be sleek and classy"; *requirements to convey brand emotions/feel*, such as "I'd like the logo to convey happiness and excitement." We validate our categories using Amazon Mechanical Turk workers (each description was classified by three workers) and find that the agreement between our classification and AMT workers' classification is 90%. To automatically classify task descriptions for all 5,737 contests, we use the methods described in Online Appendix A.

3.2. Complexity of Design Images

Pieters et al. (2010) and van Grinsven and Das (2016) use human raters to measure perceptions of ads and logo complexity. Because we have 425,475 design images in

Table 1. Descriptive Statistics for the Main Variables in the Data Set

Name	Description	Mean	Standard deviation	Minimum	Maximum
Award	Contest award amount in U.S. dollars	156.93	137.6	38	2,284
Winner	A winner variable dummy indicating a winning submission in a contest	1 for 5,737 designs, 0 for 419,738 designs	Not applicable	0	1
After	A dummy variable indicating whether a date of a contest is after the AI introduction	1 if after Apr. 2018, 0 for before	Not applicable	0	1
Sub_order	Order of each submission in each contest	68.54	64.27	1	494
Experience	Designer's experience calculated as the number of days since joining the platform	323.7	269.9	0	1,964
Star	A star rating for each submission	2.87	1.26	1	5
Prop_higher-tier_before_AI	Designers' proportion of higher-tier logo contests before the AI introduction (binary)	1,180 designers, score 0; 1,194, score 1	Not applicable	0	1
Prop_non-logo_before_AI	Designers' proportion of nonlogo contests before the AI introduction (binary)	1,174 designers, score 0; 1,200, score 1	Not applicable	0	1

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Figure 1. (Color online) Example of Logos

Notes. (a) Simple logo (complexity score: 0.235). (b) Complex logo (complexity score: 2.05).

our data set, it would be infeasible to manually classify all these images as more complex or less complex. Hence, we use a measure widely used in computer science literature to measure image complexity: spatial information (SI) complexity (Yu and Winkler 2013). Specifically, we use a mean of edge magnitudes from edges extracted using horizontal and vertical Sobel filters (Figure 1). The mean of edge magnitudes has shown better performance than other measures (Yu and Winkler 2013, Athar and Wang 2019).[3]

To validate this measure for the purpose of this study, we use human coders (three AMT workers classify each design) to classify 100 random designs using a Likert one to five scale (Pieters et al. 2010) with the anchor points ranging from "Very simple" to "Very complex" and check the correlation of the automated spatial information complexity measure SI with the classification scores by human raters. We find that the correlation is 0.8. It is pertinent to note that the agreement on complexity among human coders is 0.84, indicating that the automated measure is very close to human perception of complexity. Descriptive statistics on complexity is shown in Online Appendix B (Table B1).

3.3. Emotions in Design Images

To measure emotions in design submissions, we use the following methods. First, we ask Amazon Mechanical Turk workers to evaluate 2,100 design images on whether they feel any emotions by looking at the image or do not feel any emotions. Each design is evaluated by three AMT workers. Of 2,100 designs, 1,036 were evaluated as "not eliciting any emotions" (Figure 2).

Next, we use a deep learning model (using "adjective-noun pairs" features described later) that would predict each design as "eliciting emotions or not eliciting emotions." After eliminating designs with low discriminatory power, the final training set has 1,243 designs with 455 designs that belong to a category "not eliciting emotions." The model accuracy is 78.7% (with a balance for precision and recall), which is close to agreement of 80% among human raters. Thus, we use this model to predict whether a design image has emotional content or does not have it. We perform predictions for all designs in the sample.

A second measure of design emotions is more granular. We build a deep learning model for five emotions based on the largest database of 17,000 images classified by human raters into the following emotions: amusement, awe, contentment, excitement, and sadness (You et al. 2016).[4] Because this data set is unbalanced with some emotions being dominant, we create a balanced data set of 4,865 images (by using random images from larger categories) that has approximately the same number of images for each emotion category. Additionally, prior research indicates that there is an "affective" gap between low-level features of an image (such as colors) and emotions that humans perceive when they look at an image. To address the "affective gap," Borth et al. (2013) propose mid-level representations of an image based on adjective-noun pairs (ANPs). The authors use a deep learning model (SentiBank[5]) to extract 1,200 ANPs such as "colorful lights," "great adventure," and

Figure 2. (Color online) Example of Logos

Notes. (a) With emotional content. (b) Without emotional content.

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"pleasant surprise" from each image and show that those ANP pairs could be used for classifying the same set of emotions that we focus on in this study. In keeping with this, we use the SentiBank model to extract 1,200 ANPs and their probabilities for each image and retain top 10 ANPs[6] for each image to use those as features in another neural network model that classifies each design image into one of the five emotions. It is pertinent to note that we reach classification accuracy levels close to the state-of-the-art methods (Yang et al. 2017, Liu et al. 2019). Details on emotions classification are provided in Online Appendix B, Tables B1 and B2. We also use complexity and emotion measures as proxies of designers' abilities (see Tables B3 and B4 in Online Appendix B).

3.4. Classification of Designers

We track 2,374 designers who are active in both periods: before and after the AI launch. The first group includes designers who participated mostly in lower-tier less-complex logo design contests before the AI launch (we term them lower-tier designers). The second group of designers participated in both lower-tier logo contests and higher-tier logo contests before the AI launch (we term them cross-tier designers). Additionally, designers in the third group participated in both logo and nonlogo contests before the AI launch (we term them cross-category designers). As a proxy for the abilities of these designers, we measure the emotions and complexity of designers' submissions in these three groups before the AI system launch (see Table B3 in Online Appendix B). As expected, the lower-tier designers have the lowest emotions and complexity values followed by cross-tier designers, whereas cross-category designers have the highest emotions and complexity of designs among the three groups.

3.5. Successful and Unsuccessful Designers

To understand behaviors of successful and unsuccessful designers, first we define these groups of designers. It is pertinent to note that the successful designers include designers who were winning before the AI system launch (and keep winning after the AI launch) and new winners, whereas all other designers are categorized as unsuccessful (unsuccessful after the AI launch). Thus, we consider the following groups of designers as *successful* designers: the designers who did not win before the AI launch and who start winning, that is, have at least one win, after the AI launch ("losers before AI – winners after AI"); the designers who won at least once before the AI launch, and who won at least once after the AI launch ("winners before AI – winners after AI"). Because there are no substantial differences in the results for the group "winners before AI – winners after AI," and "losers before AI – winners after AI" (see Online Appendix F, Tables F5, F6, and F7), we combine these two groups into a group of *successful* designers for simplicity of reporting. Similarly, we consider the following groups of designers as *unsuccessful* designers: the designers who did not win before the AI launch and still do not win after the AI launch ("losers before AI – losers after AI") and the designers who won at least one time before the AI launch, and do not win after the AI launch ("winners before AI – losers after AI"). Because there are no substantial differences in results for the group "losers before AI – losers after AI" and "winners before AI – losers after AI" (see Online Appendix F, Tables F5, F6, and F7), we combine these two groups into a group of *unsuccessful* designers for simplicity of reporting. Additionally, the successful designers in each group have higher abilities (compared with the unsuccessful designers) as measured by emotions and complexity of designs. Furthermore, the successful (unsuccessful) cross-tier designers and cross-category designers have higher emotions and complexity in their design submissions compared with the successful (unsuccessful) lower-tier designers (see Table B4 in Online Appendix B).

4. Methodology and Models

4.1. Impact of AI on Designers

To address the first research question relating to how designers respond to the AI system launch, we first compare the attrition rates of designers in different types of contests and in different groups of designers before and after the AI launch. For that purpose, we calculate the number of distinct designers participating in lower-tier, higher-tier, and nonlogo contests six months before the AI launch and compare that to the number of the same designers still participating in those contests one month before the AI launch. Similarly, we calculate the number of distinct designers participating in lower-tier, higher-tier, and nonlogo contests one month after the AI launch and compare that to the number of the same designers still participating in those contests six months after the AI launch. We obtain similar results if we calculate the attrition rates in two-month periods (five to six months before AI versus one to two months before AI, one to two months after AI versus five to six months after AI). Additionally, we calculate the attrition rates for the three groups of designers: lower-tier designers, cross-tier designers, and cross-category designers.

Next, we track the switching behaviors of designers in response to the threat of AI. To do so, for each group of designers, we calculate the number of lower-tier contests, higher-tier contests and nonlogo contests in which the designers participate in after the AI system introduction. We define "switching" as an increase (by at least 1%) in the proportion of contests (higher-tier logo contests or nonlogo contests) in which each designer participates in after the AI launch. By tracking the designers' switching, we seek to understand whether the designers' abilities (as demonstrated by participation

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in more-complex higher-tier logo contests or nonlogo contests before the AI launch) determine the switching response to the threat of AI. To test this, we calculate the proportion of higher-tier or nonlogo contests that each designer participated in before the AI system introduction (Table 1) and use the switching to higher-tier or nonlogo contests as binary outcomes (see Section 5).

4.2. Comparing Successful and Unsuccessful Designers

To address the second research question, we compare the responses of successful and unsuccessful designers to the threat of AI. We seek to understand whether designers change their participation in contests and their number of submissions and whether the successful designers are different in their behaviors from the unsuccessful designers. Additionally, we seek to understand whether designers change emotional expression and complexity of designs in response to the AI system launch. The empirical model has the following form:

$$Y = \mathrm{After}_t + \alpha_d, \tag{1}$$

where Y is the dependent variable (first set of variables of interest, the number of contests per designer per day, number of submissions per designer per contest; second set, emotions and complexity of designs); After_t is a dummy variable indicating a period after the introduction of the AI system; and α_d are designer fixed effects. The descriptive statistics for the dependent variables are shown in Table 2.

4.2.1. Additional Controls with PSM. We add several additional controls that could affect the results. For example, the AI system might have changed competition in contests or changed contests' task requirements due to partial cannibalization of lower-tier logo contests (see Section 5). Additionally, some designers change their contest choices after the AI introduction by switching to higher-tier logo contests or to contests in other nonlogo categories. Those changes might be responsible for some of the effects, so we control for those changes to isolate the effect of the "threat" of AI.

4.2.2. Control for Changes in Competition. The AI system launch might have changed competitive dynamics in contests. If competition in contests changes after the AI launch, designers might respond to changes in competition rather than to the AI system. To account for this, we first check whether increased competition has an impact on the dependent variables of interest such as emotional content and complexity of designs. We find that when the number of available contests, number of designers and design submissions increase, designers do not significantly change emotional content and complexity of their designs. This result is supported for both successful and unsuccessful designers: both before the AI launch and after the AI launch (see Online Appendix C, Table C1). Nevertheless, we still control for changes in competition. To do so, we use propensity score matching (Rosenbaum and Rubin 1983) to match contests before and after the AI launch on such variables as the number of designers and the number of design submissions in each contest.

4.2.3. Control for Changes in Task Requirements. If task requirements change in contests after the AI system launch, designers might change their behaviors because of those changes. In examining the impact of task requirements' changes, we find that if task requirements increase, the emotions and complexity increase by a small amount (see Online Appendix C, Table C2). To control for changes in task requirements, we match contests (using PSM) before and after the AI launch on these three classes of requirements: specific requirements, abstract requirements, and requirements to convey brand emotions/feel.

4.2.4. Control for Choice of Contests (Switching). In addition, cross-tier designers and cross-category designers might change their strategies because they switch to contests with more-complex requirements after the AI

Table 2. Comparison Between the Focal Platform with AI and the Control Platform Without AI

Platform	Number of contests per designer per day	Number of submissions per designer per contest	Complexity	Emotions binary	Amusement	Awe	Contentment	Excitement	Sad
Focal platform	3.97 (3.24)	4.17 (4.74)	0.887 (0.741)	268,049 designs, 1; 157,426 designs, 0	1.35 (1.65)	0.319 (0.99)	1.75 (1.91)	3.63 (3.38)	3.6 (3.7)
Control platform	3.73 (3.09)	4.71 (5.63)	0.74 (1.02)	155,514, 1; 74,680 designs, 0	1.41 (1.32)	0.34 (0.74)	1.66 (1.48)	3.49 (2.08)	3.09 (2.2)

Notes. Mean values are outside parentheses. Standard deviations are inside parentheses. Emotions (amusement, awe, contentment, excitement, sadness) are in percentage scale 0 to 100.

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system launch. To address this issue, we compare only matched logo contests in the higher-tier for cross-tier designers and matched logo contests for cross-category designers before and after the AI launch.

The formula for calculating propensity scores for matching contests before and after AI (Austin 2011) is

$$e1 = \Pr(Z = 1 \mid X1), \tag{2}$$

where e1 is propensity score of being in the period after the AI introduction; Pr is the probability of being in the treatment group, where treatment is the period after the AI introduction; Z is the period After the AI introduction; and X1 are covariates such as the number of designers in each contest and the number of design submissions in each contest: specific requirements, abstract requirements, and requirements to convey brand emotions/feel. For this PSM matching procedure, we use the nearest neighbor one-to-one matching with the logit function and no replacement. We find that matching variables (X1) for treatment and control periods (after AI versus before AI) are not statistically different after the matching (see Table E1 in Online Appendix E), which provides additional support for the matching procedure. We use PSM to match contests before and after the AI launch to isolate the effect of the "threat of AI."

A second matching procedure is to use the sample of retained matched contests (before AI and after AI) and to match designers in the treatment groups (in logo contests) and in the control groups (in nonlogo contests on the same platform or in logo contests on another platform) for the DiD analyses described in the next section.

The formula for calculating propensity scores for matching designers in treatment and control groups is

$$e2 = \Pr(T = 1 \mid X2), \tag{3}$$

where e2 is the propensity score of being in the treatment group (designers in logo contests); Pr is the probability of being in the treatment group; and T is the treatment group (designers in logo contests), whereas the first control group includes designers in nonlogo contests, and the second control group includes designers in logo contests on another platform (without AI); X2 are the covariates such as experience of designers in each contest (in days) and the number of design submissions by designer by contest. For the PSM, we use the nearest neighbor one-to-one matching with the logit function. We find that matching variables (X2) for the treatment and control groups are not statistically different after the matching (see Table E2 in Online Appendix E).

4.3. DiD Analysis with PSM

To support the causal identification of the effects, we use a DiD model with PSM techniques (Smith and Todd 2005). The general formula is as follows:

$$Y = \mathrm{PSM}\big(\mathrm{After}_t + \mathrm{Treatment\_group} + \mathrm{After}_t \times \mathrm{Treatment\_group}\big), \tag{4}$$

where Y is the dependent variable (the number of contests per designer per day, number of submissions per designer per contest, emotions, and complexity of designs); PSM is propensity score matching; After_t is a dummy variable indicating a period after the AI system launch; and Treatment_group is the group of designers that were affected by the introduction of the AI system for logo design.

The first control group in this case includes designers who always participate in nonlogo contests both before and after the introduction of the AI system. Because the AI system is designed for logo design only, designers participating in nonlogo contests should not be affected by the AI system for logo design. For the matched control group, we restrict the sample to only successful designers when we perform analyses for the responses of successful designers. Similarly, we restrict the sample to only unsuccessful designers in both treatment and control groups when we perform analyses for the responses of unsuccessful designers. First, we match contests before and after the AI launch using Equation (2). To control for contest switching, we match only higher-tier contests before and after the AI launch when we perform analyses for cross-tier designers. Similarly, we match only logo contests before and after the AI launch when analyzing cross-category designers. Furthermore, it is pertinent to note that designers in the control group could be affected by "switching" designers. We exclude these "switchers" to nonlogo contests after the AI launch from nonlogo contests (i.e., from the control group) and find the results to be consistent with our main findings. Finally, we match designers in treatment and control groups using Equation (3).[7] The purpose of the matching is to compare treatment and control groups in very similar contest conditions and for very similar designers to isolate the effect of the AI "threat" on designers' changes in behaviors and strategies.

Additionally, we use a second control group: a new crowdsourcing platform where we download only logo design contests for the same period, namely, from October 2017 until September 2018. This approach has been implemented in prior information systems research (Khern-am-nuai et al. 2018).

There are a total of 959 contests and 230,194 design submissions made by 6,021 designers for that period. We use PSM to match contests and designers on both platforms to make sure that we compare similar designers in similar contest conditions. Table 2 shows comparison of a focal platform with AI with the control platform without AI.

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5. Results

5.1. Effects of AI on the Number and Composition of Contests

First, we compare the number of lower-tier logo contests (with the award below the median value of 110 US dollars), the number of higher-tier logo contests, and the number of nonlogo contests before and after the AI launch. Results indicate that after the introduction of the AI system for logo design the number of lower-tier contests for logo design decreases by 25%, whereas the number of higher-tier contests for logo design decreases by 5%. In contrast, the number of nonlogo contests increases by 10%.

5.2. Designers' Responses to the Launch of the AI System for Logo Design

We seek to understand the behaviors of designers in response to the introduction of the AI system. First, we compare the attrition rate in contests. We find that after the AI launch the attrition rate increases from 65% to 69.7% (the difference is 7.23%) in the lower-tier logo contests, decreases from 59% to 57.45% (the difference is 2.6%) in the higher-tier logo contests, and increases marginally from 79% to 80% (the difference is 1.26%) in the nonlogo contests. Because the attrition rate increases only in lower-tier logo contests, we check and confirm that the attrition rate increases among lower-tier designers, that is, designers with lower abilities who participated mostly in lower-tier logo contests before the AI launch.

Next, we track the switching behaviors of the three groups of designers. We find that designers switch primarily in one direction after the AI introduction to either higher-tier logo contests or to nonlogo contests, whereas only 3% of designers switch in both directions simultaneously. Although other "switching" directions are possible (i.e., switching from higher-tier logo contests to lower-tier logo contests), their instances are very rare. Additionally, there is a group of designers (about 10% of designers, or 240 designers who made 6,451 design submissions) who participated only in nonlogo contests both before and after the introduction of the AI system. We use the designers in that group as a control group in the DiD models with PSM (Smith and Todd 2005).

To understand switching preferences of designers in response to AI, we match designers on their experience and their activity (number of submissions) on the platform using PSM and dichotomize proportions of higher-tier logo contests and nonlogo contests (before the AI launch) by median splits (Tables 1 and 3).

We find that cross-tier designers who had prior exposure to higher-tier contests (i.e., higher proportion) before the AI launch are more likely to switch to higher-tier logo contests, whereas cross-category designers who had prior exposure to nonlogo contests prior to the AI launch are more likely to switch to nonlogo contests after the introduction of the AI system compared with the lower-tier designers who are more likely to continue to participate in lower-tier logo contests. The unit of analysis in this model is each designer's proportion of higher-tier or nonlogo contests before the AI launch.

5.3. Successful Designers' Responses to the Introduction of the AI System for Logo Design

Next, we seek to understand how the behaviors of successful designers differ from the behaviors of the other designers after the AI system launch. Specifically, we test whether successful and unsuccessful designers behave differently with respect to contest participation behavior, that is, the number of contests that each designer participates in per day and the number of design submissions per contest (Tables 4–7). Next, we test whether successful and unsuccessful designers change such design attributes as emotional expression and complexity in their responses to the introduction of the AI system (Tables 8–12).

Tables 4 and 5 (first three columns) compare the successful and the unsuccessful designers before and after the AI launch in models with designer fixed effects. It is pertinent to note that the unit of analysis in Tables 4 and 5 is designer-contest-day, that is, how many contests a designer participates in per day.

Tables 6 and 7 show how the number of submissions change after the AI introduction. It is pertinent to note that the unit of analysis in these tables is each designer's total design submissions in each contest.

The results (Tables 5 and 7, first three columns) show that the *unsuccessful* designers participate in more contests after the AI launch (increases by 15% for lower-tier designers, by 14% for cross-tier designers, and by 13.3% for cross-category designers) and either decrease or do

Table 3. Propensity Score Matching Model for Designers' Switching Behaviors After the AI Launch

Dependent variables are binary variables for switching	Switching to higher-tier logo contests from lower-tier (after AI)	Switching to nonlogo contests from lower-tier (after AI)
Prop_higher-tier_before_AI$_{cd}$	0.059*** (0.0044)	
Prop_non-logo_before_AI$_{cd}$		0.209*** (0.033)
Sample size	1,254	1,107

Note. Subscript c denotes contests; subscript d denotes designers.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; ns, not significant.

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Table 4. Number of Contests Before and After AI for the Three Groups of Successful Designers

Dependent variable is number of contests (Y_{cdt})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{dm}$ for DID)	−0.21***	−0.041^{ns}	0.22^{ns}	−0.0858^{ns}	0.4^{ns}	0.142^{ns}	0.043^{ns}	0.063***	−0.17***
	(0.03)	(0.043)	(0.401)	(0.203)	(0.258)	(0.186)	(0.051)	(0.0182)	(0.012)
Constant	2.86***	3.05***	2.649***	2.4***	2.3***	2.14***	3.112***	3.21***	3.15***
	(0.22)	(0.305)	(0.266)	(0.36)	(0.047)	(0.15)	(0.0075)	(0.0065)	(0.007)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	119	103	63	—	—	—	—	—	—
Sample size	18,450	20,730	15,915	27,920	26,852	22,540	15,036	14,468	14,602

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript dm denotes matched designers in treatment and control groups, and subscript cdt denotes number of contests per designer per day.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; ns, not significant.

not change the number of submissions per contest (decreases by 31% for lower-tier designers, does not change for cross-tier designers and for cross-category designers). In contrast, the *successful* designers (Tables 4 and 6, first three columns) almost do not change the number of contests that they participate in after the AI launch (all changes are less than 1%). However, they substantially increase the number of submissions per contest (increases by 60% for lower-tier designers, by 30% for cross-tier designers, and by 55.7% for cross-category designers).

Next, we seek to understand whether successful designers and unsuccessful designers increase emotional content and complexity of design submissions in response to the introduction of the AI system.[8] It is pertinent to note that the unit of analysis is complexity and presence of emotions (or five emotions) aggregated for each designer for each contest. For each designer we measure complexity and emotions of each design image submitted in each contest and compute an average value per designer per contest.

Interestingly, we find that the successful designers increase emotional content and complexity of designs (Tables 8 and 9, first three columns) after the AI system launch across all three groups of designers.

The logit model with five emotions (Table 10, first three columns) shows that all three groups of successful designers increase the "excitement" of their design submissions after the AI launch.

As for the effect sizes, successful lower-tier designers increase emotional content by 5.6% and complexity by 7.5% after the AI launch. Successful cross-tier designers increase emotional content by 6% and complexity by 11.57% after the AI launch, and successful cross-category designers increase emotional content by 9.81% and complexity by 17.1% after the AI launch.[9]

Additionally, we find that the unsuccessful designers in all three categories do not change emotions in their designs (Table 11) and do not change complexity of their designs (Table 12) after the AI launch.

The granular model with five emotions also shows that the unsuccessful designers in all three categories do not change emotional content of their design submissions (see Online Appendix F, Table F12).

To confirm all the results, we use DiD models with propensity score matching (PSM-DID1 and PSM-DID2

Table 5. Number of Contests Before and After AI for the Three Groups of Unsuccessful Designers

Dependent variable is number of contests (Y_{cdt})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{dm}$ for DID)	0.55***	0.524***	0.56***	0.329**	0.222*	0.4*	0.48***	0.196***	0.7445***
	(0.016)	(0.0213)	(0.06)	(0.167)	(0.121)	(0.22)	(0.025)	(0.0272)	(0.0292)
Constant	3.99***	3.37***	3.71***	2.99***	2.32***	3.27***	3.495	3.62***	3.63***
	(0.32)	(0.3)	(0.399)	(0.02)	(0.083)	(0.065)	(0.007)	(0.0073)	(0.0075)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	477	450	263	—	—	—	—	—	—
Sample size	44,618	29,365	27,158	61,185	58,498	34,937	31,888	18,405	18,033

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript dm denotes matched designers in treatment and control groups, and subscript cdt denotes number of contests per designer per day.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; ns, not significant.

Table 6. Number of Submissions Before and After AI for the Three Groups of Successful Designers

Dependent variable is number of contests (Y_{sdc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	3.58*** (0.443)	1.832*** (0.121)	3.34*** (0.36)	1.121* (0.63)	3.7*** (1.19)	6.7*** (1.98)	0.703*** (0.087)	0.61*** (0.33)	0.785*** (0.22)
Constant	4.02*** (0.49)	3.08*** (1.359)	3.72*** (1.15)	4.93*** (0.55)	5.19*** (0.55)	4.8*** (0.49)	4.64*** (0.013)	3.36*** (0.009)	4.75*** (0.021)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	104	122	82	—	—	—	—	—	—
Sample size	23,783	27,779	22,589	11,210	10,087	8,930	22,331	16,037	17,411

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript s denotes submissions, subscript cd denotes matched contests and designers in treatment and control groups, and subscript sdc denotes number of submissions per designer per contest.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; ns, not significant.

in Tables 4–12). An important test for the DiD method is a test of parallel trends before the treatment (Autor 2003). We perform the tests for each group (lower-tier designers, cross-tier designers, and cross-category designers) by interacting the treatment group with the monthly dummies in the period before the AI system launch (periods from $t-6$ to $t-1$) and find that the slopes for the treatment and control groups are not significantly different, which confirms the parallel trends assumption (see Tables E3, E4 and E5 in Online Appendix E).

After the matching (see Section 4), we perform DiD analyses on the matched groups with two different control groups (see models PSM-DID1 and PSM-DID2 for the first and second control groups in Tables 4–12, and the full DiD results are reported in Online Appendix F in Tables F1–F4 and F8–F14).

We use DiD methods to confirm prior results regarding the number of contests that each designer participates in per day before and after the AI launch, the number of submissions per designer per contest before and after the AI introduction, and emotions and complexity of designs. It should be noted that we report the results for the DiD models without user or time fixed effects but adding the user and time (month) fixed effects provides consistent estimates.

5.4. Robustness Checks

We perform additional robustness checks to support the results. First, we compare short periods of two months before and two months after the AI system launch and find that the results are highly consistent with the longer periods of six months before and six months after the AI launch. As a falsification test, we compare the period of three to four months (and five to six months) before the AI launch with the period of one to two months before the AI launch. In the latter case, since the AI was not introduced at that time, there should be no change in emotions and complexity of designs even among the successful designers, and we confirm that this is the case. Additionally, the switching patterns observed on

Table 7. Number of Submissions Before and After AI for the Three Groups of Unsuccessful Designers

Dependent variable is number of contests (Y_{sdc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	−1.54*** (0.0235)	0.054^{ns} (0.05)	0.1^{ns} (0.18)	0.3776^{ns} (0.237)	0.6^{ns} (0.44)	0.081^{ns} (0.088)	−0.21*** (0.019)	0.104^{ns} (0.113)	0.305^{ns} (0.229)
Constant	4.06*** (0.23)	2.87*** (0.91)	4.3*** (0.81)	4.27*** (0.07)	4** (1.51)	4.38*** (0.77)	2.875*** (0.0057)	2.63*** (0.007)	2.93*** (0.021)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	495	558	306	—	—	—	—	—	—
Sample size	60,118	46,442	39,391	58,995	52,074	18,544	34,978	17,148	18,461

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript s denotes submissions, subscript cd denotes matched contests and designers in treatment and control groups, and subscript sdc denotes number of submissions per designer per contest.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; ns, not significant.

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Table 8. Emotions Before and After the AI Launch for the Three Groups of Successful Designers

Dependent variable is number of contests (Y_{dc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	0.26*** (0.029)	0.37*** (0.038)	0.577*** (0.035)	0.261** (0.129)	0.43** (0.19)	0.478** (0.22)	0.149*** (0.0266)	0.153*** (0.0473)	0.146*** (0.033)
Constant	1.21*** (0.113)	1.48*** (0.117)	1.37*** (0.14)	2.75*** (0.27)	1.3*** (0.031)	0.955** (0.467)	1.06*** (0.008)	0.998*** (0.0088)	0.984*** (0.0097)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	126	102	73	—	—	—	—	—	—
Sample size	29,072	21,773	20,953	17,823	15,086	14,337	19,938	15,520	14,372

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript cd denotes matched contests and designers in treatment and control groups, and subscript dc denotes average emotions for all submissions per designer per contest.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; ns, not significant.

the focal platform after the AI system introduction, are not observed in the periods before the AI system introduction.

Because we find that the successful designers increase the number of submissions per contest after the AI launch, we also check whether the number of submissions is associated with the improvement in quality for the designers after the AI launch. We find that the successful designers increase emotional content of their designs with each additional submission (increases by 2.02% for each resubmission in the lower-tier designers' group, increases by 2.27% for each resubmission in the cross-tier designers' group and increases by 2.33% for each resubmission in the cross-category designers' group) and increase complexity of their designs with each additional submission (increases by 2.15% for each resubmission in the lower-tier designers' group, increases by 2.42% for each resubmission in the cross-tier designers' group, and increases by 2.97% for each resubmission in the cross-category designers' group). In contrast, the unsuccessful designers do not increase emotions and complexity with each additional submission.

An alternative explanation for the increase in the number of submissions per contest by the successful designers as a response to the AI system could be the differences in feedback patterns after the AI launch as compared with the period before the AI launch. First, we compare high-star feedback frequency before and after the AI launch and find that the feedback frequency changes only marginally after the AI launch. Next, as a robustness check, we also match contests before and after the AI launch on the number of high-star ratings provided by contest holders to each designer and find the results to be consistent.

5.5. Survey of Designers

To understand whether designers feel the threat of AI and to confirm behavioral changes reported in our empirical findings, we conduct an Amazon Mechanical Turk survey of 100 designers. The survey was completed by 96 designers. More details about the survey are available in the Online Appendix G (Tables G1, G2, and G3; Figure G1). We find that the vast majority of

Table 9. Complexity Before and After the AI Launch for Three Groups of Successful Designers

Dependent variable is number of contests (Y_{dc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	0.058*** (0.009)	0.11*** (0.008)	0.14*** (0.01)	0.068** (0.031)	0.197*** (0.068)	0.224*** (0.07)	0.148*** (0.0086)	0.0652* (0.037)	0.121*** (0.01)
Constant	0.747*** (0.0564)	0.98*** (0.056)	0.84*** (0.077)	1.72*** (0.047)	1.117*** (0.058)	1.779*** (0.101)	0.75*** (0.0025)	0.506*** (0.003)	0.685*** (0.0032)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	126	102	73	—	—	—	—	—	—
Sample size	28,877	21,251	20,814	17,123	14,987	14,149	19,365	15,173	14,044

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript cd denotes matched contests and designers in treatment and control groups, and subscript dc denotes average emotions for all submissions per designer per contest.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; ns, not significant.

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Table 10. Five Emotions Before and After the AI Launch for the Three Groups of Successful Designers

Dependent variable is one of the five emotions (Y_{dc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ or $After_t \times Treatment_{cd}$ for DID (amus.)	-0.015^{ns} (0.028)	-0.003^{ns} (0.04)	0.078^{ns} (0.054)	-0.07^{ns} (0.084)	0.064^{ns} (0.078)	0.293^{ns} (0.303)	-0.024^{ns} (0.0278)	-0.018^{ns} (0.0468)	0.026^{ns} (0.0325)
$After_t$ or $After_t \times Treatment_{cd}$ for DID (awe)	0.015^{ns} (0.019)	-0.034^{ns} (0.026)	-0.023^{ns} (0.025)	0.0198^{ns} (0.054)	-0.144^{ns} (0.171)	0.051^{ns} (0.232)	-0.0018^{ns} (0.0183)	-0.143^{ns} (0.281)	-0.0425^{ns} (0.03)
$After_t$ or $After_t \times Treatment_{cd}$ for DID (content.)	-0.028^{ns} (0.035)	-0.013^{ns} (0.045)	-0.107^{ns} (0.109)	-0.2^{ns} (0.17)	0.06^{ns} (0.11)	0.079^{ns} (0.339)	-0.11^{ns} (0.09)	-0.0528^{ns} (0.052)	-0.136^{ns} (0.137)
$After_t$ or $After_t \times Treatment_{cd}$ for DID (excit.)	0.170*** (0.057)	0.307*** (0.043)	0.471*** (0.067)	0.46* (0.25)	0.81** (0.41)	0.74** (0.36)	0.44*** (0.0584)	0.299*** (0.0932)	0.358*** (0.0636)
$After_t$ or $After_t \times Treatment_{cd}$ for DID (sadness)	0.11^{ns} (0.084)	0.046^{ns} (0.085)	0.042^{ns} (0.077)	0.255^{ns} (0.21)	-0.2^{ns} (0.218)	-0.386^{ns} (0.758)	0.113^{ns} (0.0783)	0.226^{ns} (0.21)	0.348^{ns} (0.272)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	126	102	73	—	—	—	—	—	—
Sample size	29,015	21,452	20,741	17,717	15,017	14,122	19,021	15,301	14,121

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript cd denotes matched contests and designers in treatment and control groups, and subscript dc denotes average emotion (one of the five emotions) for all submissions per designer per contest.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; ns, not significant.

designers (87.5%) perceive the threat of the AI system with the mean threat score of 3.25 on a scale of one to five ("nonthreatening" to "very threatening"), and their potential actions match with those that we find in the empirical analyses and match with the PMT model. Specifically, 31 designers respond that they will avoid the threat of AI by leaving the platform. Fifty-three (53) designers respond that they will improve logo designs to make them better than the AI-generated logo designs. More-experienced designers are more likely to improve logo designs (average experience score is 2.5 in that group on a scale from "1–beginner" to "3–expert designer"). In contrast, less-experienced designers are more likely to avoid AI by leaving the platform (average experience score is 2.07 in that group on a scale from "1–beginner" to "3–expert designer"). The difference between expertise scores in the two groups is statistically significant. Interestingly, when we ask an open-ended question about how designers would change their designs in response to AI, 7 designers mention that they will increase the complexity of designs. Examples are as follows: "I would probably make them more complex … by adding more elements", "I would probably add some slight imperfections and asymmetries,"[10] "I feel like I

Table 11. Emotions Before and After the AI Launch for the Three Groups of Unsuccessful Designers

Dependent variable is emotions binary (Y_{dc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	0.034^{ns} (0.023)	0.014^{ns} (0.03)	0.05^{ns} (0.04)	-0.053^{ns} (0.047)	-0.003^{ns} (0.23)	0.232^{ns} (0.159)	-0.086^{ns} (0.077)	-0.105^{ns} (0.075)	-0.022^{ns} (0.0199)
Constant	1.35*** (0.088)	1.55*** (0.114)	1.5*** (0.13)	1.11*** (0.009)	2.36*** (0.158)	2*** (0.085)	0.856*** (0.0053)	0.69*** (0.0067)	0.698*** (0.0067)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	604	462	319	—	—	—	—	—	—
Sample size	60,044	31,687	18,934	71,365	38,785	15,391	34,471	28,616	24,988

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript cd denotes matched contests and designers in treatment and control groups, and subscript dc denotes average emotions for all submissions per designer per contest.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; ns, not significant.

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Table 12. Complexity Before and After the AI Launch for the 3 Groups of Unsuccessful Designers

Dependent variable is complexity (Y_{dc})	Lower-tier	Cross-tier	Cross-category	Lower-tier (PSM – DID1)	Cross-tier (PSM – DID1)	Cross-category (PSM – DID1)	Lower-tier (PSM – DID2)	Cross-tier (PSM – DID2)	Cross-category (PSM – DID2)
$After_t$ (or $After_t \times Treatment_{cd}$ for DID)	-0.006^{ns} (0.0057)	-0.02^{ns} (0.012)	-0.008^{ns} (0.0059)	-0.047^{ns} (0.078)	-0.12^{ns} (0.0787)	-0.15^{ns} (0.25)	-0.05^{ns} (0.065)	-0.043^{ns} (0.0528)	-0.028^{ns} (0.06)
Constant	0.892*** (0.049)	0.95*** (0.061)	0.972*** (0.0123)	0.877*** (0.0029)	1.51*** (0.034)	1.21*** (0.014)	0.61*** (0.0018)	0.449*** (0.002)	0.449*** (0.0022)
Designer fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
No. of designers	604	462	319	—	—	—	—	—	—
Sample size	59,523	31,125	18,447	70,901	38,221	14,898	33,644	28,062	24,560

Note. Subscript t denotes time, subscript d denotes designers, subscript c denotes contests, subscript cd denotes matched contests and designers in treatment and control groups, and subscript dc denotes average emotions for all submissions per designer per contest.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; ns, not significant.

would add components that AI might not grasp. Visual metaphors for instance. I feel like AI-generated logos would be simplistic in general," and "I would pick something with more design elements." Additionally, 10 other designers mention that they will focus on emotional content of designs. Examples of such comments are as follows: "I would add more emotion to my work … ," "I can give emphasis to the logo from a sentimental aspect, adding loads of happiness … ," "I have the ability to look more deeply into the emotional content that a client may be looking for," and "AI is not able to capture feeling or warmth when creating, and that is the strength I have as a human." More details are provided in Online Appendix G (Table G3).

6. Implications and Conclusion

This study seeks to understand the overall impact of the AI logo system on the contests available on the crowdsourcing platform and on designers' strategies in response to the AI system launch. As noted earlier, AI systems are different from prior generations of technologies in their impact on humans' behaviors and strategies. Given that prior technologies are superior to humans in routine and standardized tasks, the only option for humans is to quit those tasks or switch to other tasks. However, AI systems simulate nonroutine tasks when "tacit" human knowledge is required. Humans can quit those tasks, or they can compete with the AI systems by leveraging their creativity, imagination, emotional expression, empathy, and so on.

We find that the AI system "cannibalizes" lower-tier logo contests with less-complex requirements to a greater extent as compared with higher-tier logo contests with more-complex requirements. We find that different groups of designers respond differently to the introduction of the AI system. The lower-tier designers in the first group either leave the platform or continue to participate predominantly in lower-tier logo contests, whereas the cross-tier designers and cross-category designers switch to higher-tier logo contests or to nonlogo contests accordingly. We find that designers who had prior exposure to higher-tier logo contests or nonlogo contests are more likely to switch to higher-tier or to nonlogo contests accordingly. We use a "before-after" analyses with designer fixed effects and use propensity score matching and difference-in-differences models to support causal identification of the effects. Interestingly, we find that the successful designers become more focused and increase the number of submissions per contest substantially (by 30%–60% depending on a group of designers) compared with the unsuccessful designers after the AI launch. In contrast, the unsuccessful designers participate in more contests after the AI launch (by 13%–15%) and either decrease the number of submissions per contest (in the lower-tier designers' group) or do not change the number of submissions per contest (in the groups of cross-tier designers and cross-category designers). Furthermore, we find that the successful designers, compared with the unsuccessful designers, in all three groups increase emotional content (by 5.6%–9.81% depending on a group of designers) and complexity (by 7.5%–17.1% depending on a group of designers) of design submissions as a response to the introduction of the AI system. Finally, we find that the AI system's designs are different from human designs (see Online Appendix B, section "Comparison of Human Logo Designs with the AI System Logo Designs"). With respect to emotions, humans can produce logos with more positive emotions and fewer neutral emotions as well as generate emotions with higher intensity as compared with the AI system. The AI system also has an upper limit of complexity, and about half of the designers on the platform can produce designs that have higher complexity compared with the AI complexity.

This study has important implications for theory and practice. First, prior research on the effects of AI adoption on employment has mostly been conducted at the industry or geographic region level, and the effects on employment are found to be negative. More recent

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studies at the firm level (Dixon et al. 2019) point to more nuanced effects, when AI systems increase overall employment, but negatively affect employment of managers. This study contributes to this research stream by expanding the context of AI to crowdsourcing platforms. To the best of our knowledge, this study is among the first to explore users' successful strategies and responses to the introduction of an AI system in a decentralized platform.

Second, prior research has mostly used surveys to understand responses of employees to the adoption of AI systems at their workplace. The findings from prior studies are context specific. Some employees, for instance, disability care workers feel less "threat" from smart AI robots because they think that these AI robots are not advanced in emulating human touch and emotions (Wolbring and Yumakulov 2014). In contrast, in the hotel industry, employees feel more job insecurity in response to AI systems' adoption and are more likely to quit (Li et al. 2019). This study extends this line of research into empirical setting. The results show that successful designers respond to the AI system by focusing on each contest (i.e., making more submissions per contest) and by increasing emotional content and complexity of their designs.

The findings of this study also contribute to the theory of threat by expanding the protection motivation theory to a new context of the threat of AI. In keeping with the theoretical predictions, we find that designers respond to the threat of AI differently based on their abilities. Designers in nonlogo contests who are far removed from the locus of the threat do not change their behaviors. In contrast, the designers closest to the locus of threat, designers with low coping abilities in lower-tier less-complex contests, are more likely to leave the platform after the AI launch. Designers on the platform who perceive the threat from AI and who have higher coping abilities respond directly to the threat from AI by moving away from the locus of the threat to higher-tier or nonlogo contests as well as by adapting their design submissions. Among these, the successful designers who have the highest coping abilities adapt more effectively as compared with the other designers. To the best of our knowledge, this is one of the first papers that provides large-scale empirical evidence of individuals' differing responses to the threat of AI based on their abilities.

Our findings contribute to the research related to design emotions and complexity. Prior research has studied these variables in laboratory settings (van Grinsven and Das 2016, De Bajaj and Bond 2018, Marchis et al. 2018). Additionally, Berlyne's model of esthetic perception considers emotions and complexity as the two key variables. To the best of our knowledge, this study is among the first to measure design emotions and complexity empirically on a large scale in a decentralized platform for design crowdsourcing.

The findings of this study also have valuable practical implications. Managers can use our findings to understand "cannibalization" patterns when AI replaces simple contests with human designers. Additionally, our findings provide insights into strategic behaviors of users on crowdsourcing platforms in response to the adoption of an AI system. Specifically, managers should be aware that after the introduction of the AI system designers start shifting from the locus of the threat of AI to other contests not directly threatened by the AI system and that successful designers improve quality (esthetics) of designs by focusing on design elements differentiating them from the AI system. Overall, because AI replaces the least skilled designers with the lowest abilities (who leave the platform), the overall quality of remaining designers is expected to increase. Furthermore, our findings can help managers to better segment clients into groups based on their preferences for the AI system or human designers. Importantly, market providers can use our findings to optimize revenue from both sources, AI and human designers, by designing flexible pricing and marketing mechanisms. Another source of revenue could be a hybrid model when a client starts using the AI system, and then an expert designer finalizes the design. Additionally, in the presence of the AI system managers might offer new incentives to designers to reduce turnover rates. Finally, knowledge of the capabilities and limitations of AI systems for design might be helpful for human designers who can leverage such design attributes as emotions and complexity to improve their outcomes.

This study is not without limitations. First, we analyze the data on the AI system from a single crowdsourcing platform for design tasks. Future research might look at other platforms and compare the results with our findings. Second, we measure emotions and complexity of a whole image. Future research might investigate which specific parts of an image make it more "emotional" or more complex and how those parts might be related to each other and to the probability of winning a contest. Finally, future research might explore which strategies to respond to AI are better in the longer term.

Endnotes

[1] Although the extensions of the PMT theory include the concept of self-efficacy to indicate that a person has the ability to cope with the threat, this concept has been found to be correlated with actual abilities gained through prior personal experiences (Bandura 1977, 1994) and is correlated with actual abilities in specific task domains (Paunonen and Hong 2010).

[2] We verified the historical screenshots of the platform's website on the https://web.archive.org/ and found that the crowdsourcing platform's website changed immediately after the AI launch and that the AI system was showcased on the main page of the website.

[3] The SI measure does not consider color of images; Ciocca et al. (2015) have shown that color does not influence the human perception of image complexity.

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[4] You et al. (2016; see https://qzyou.github.io/) classify eight emotions: amusement, anger, awe, contentment, disgust, excitement, fear, and sadness. However, Salgado-Montejo et al. (2014) find emotions such as "fear," "anger," and "disgust" are unlikely to be present in logos. We verify that this is the case in our context as well and focus on the five emotions.

[5] See http://www.ee.columbia.edu/ln/dvmm/vso/download/sentibank.html.

[6] Using top 10 adjective-noun pairs (as opposed to top 15 or top 20, top 30, and so on) helps achieve higher accuracy of classification.

[7] For the dependent variable "number of contests per designer per day" in Tables 4 and 5, the PSM matching is done at the designer level only without matching at the contest level.

[8] Prior to this, we examine whether the emotional content and complexity of design submissions do indeed have a significant influence on the probability of winning a contest. As shown in the Online Appendix D (Tables D1 and D2), we find that both the emotional content and the complexity of the design submissions have a significant impact on the likelihood of winning a contest.

[9] Effect sizes in the logit models with binary dependent variables are estimated by comparing the probabilities of having emotions in logos before and after AI (estimated by exponentiating the intercept for the period "before AI" and dividing by one plus this exponentiated value, and estimated by exponentiating the intercept plus coefficient for "after AI" and dividing by one plus this exponentiated value for the period after AI).

[10] Asymmetries have been shown to increase complexity. See, for example, the paper by Pieters et al. (2010).

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