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HUSO 2024

Forward

The Tenth International Conference on Human and Social Analytics (HUSO 2024), held between March 10th and March 14th, 2024, continued a series of international events bridging the concepts and the communities dealing with emotion-driven systems, sentiment analysis, personalized analytics, social human analytics, and social computing.

The recent development of social networks, numerous ad hoc interest-based formed virtual communities, and citizen-driven institutional initiatives raise a series of new challenges in considering human behavior, both on personal and collective contexts.

There is a great possibility to capture particular and public opinions, allowing individual or collective behavioral predictions. This also raises many challenges, on capturing, interpreting, and representing such behavioral aspects. While scientific communities face now new paradigms, such as designing emotion-driven systems, dynamicity of social networks, and integrating personalized data with public knowledge bases, the business world looks for marketing and financial prediction.

We take here the opportunity to warmly thank all the members of the HUSO 2024 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to HUSO 2024. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the HUSO 2024 organizing committee for their help in handling the logistics of this event.

We hope that HUSO 2024 was a successful international forum for the exchange of ideas and results between academia and industry and for the promotion of progress in the area of human and social analytics.

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Table of Contents

An Investigation of How Horse Racing Experts Make Poor Decisions

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***Abstract*—In recent years, statistical researches often showed even experts can make poor decisions although they have a wealth of knowledge and experience. In this study, we focus on horse racing experts, such as racing horse owners and trainers, and investigate how and why they make poor decisions on race selections. Using sire line, distance of races, and order of finish as clues, we analyze the 36869 horses registered with Japan Racing Association (JRA) from 2010 to 2017 statistically. There are two ways horse racing experts make poor decisions on race selections: They do not select races that are likely to have good outcomes, or they select races that are likely to have poor outcomes. The results of the statistical analysis showed that horse racing experts made their poor decisions by not selecting races that are likely to have good outcomes, not by selecting races that are likely to have poor outcomes. We think this is because people are more sensitive to risks than opportunities. Even for experts, it is difficult to update knowledge and experience using good results.**

***Index Terms*—decision making; expert; Thoroughbred horse; sire line; race distance.**

I. Introduction

Unlike most of us, experts have a wealth of knowledge and experience. However, even experts can sometimes make poor decisions. For example, in the past, baseball coaches often taught players to aim for grounders rather than fly balls. However, in recent years, statistical researches brought a new batting approach that batters should aim for big fly balls rather than grounders. The new approach, known as the “fly-ball revolution”, has surprised many baseball coaches and players around the world. From the viewpoint of outcomes, there are two ways we make poor decisions:

- We do not make decisions that are likely to have good outcomes.
- We make decisions that are likely to have poor outcomes.

In the case of the “fly-ball revolution”, these two ways of making poor decisions are actually the same thing because fly balls and grounders are exclusive choices. In other words, baseball experts have only one way of making poor decisions. If we investigate a case where these two ways of making poor decisions are different, we can discuss how and why experts make poor decisions. As a result, in this study, we focus on horse racing experts, such as racing horse owners and trainers. In order to win horse races and get the prize money, they want to find races where their horses are more likely to win. There are two ways horse racing experts make poor decisions on race selections:

- They do not select races that are likely to have good outcomes.
- They select races that are likely to have poor outcomes.

Unlike in the case of the “fly-ball revolution”, these two ways of making poor decisions are different things. As a result, in this study, we intend to discuss how and why horse racing experts make poor decisions although they have a wealth of knowledge and experience. In order to analyze horse racing experts’ poor decisions, we focus on sire line, distance of races, and order of finish. A sire line is a term that refers to the paternal lineage or ancestry of a horse, especially a racehorse. Many people, especially horse racing experts, often say that a sire line can indicate the potential abilities or characteristics of a horse, such as which distance races they are good at.

The rest of this paper is organized as follows: In Section II, we survey the related works. In Section III, we survey information about racehorses and show how to collect it. In Section IV, we show how to analyze racehorse information statistically and discuss how and why horse racing experts made poor decisions. Finally, in Section V, we present our conclusions.

II. Related work

Thoroughbred horses originated from a small number of Arab, Barb, and Turk stallions and native British mares approximately 300 years ago [1]–[3]. Since then, they have been selectively bred to improve speed and stamina, and are consequently superior competitive racehorses. Wade et al. reported a high-quality draft sequence of the genome of the horse and suggested that the horse was domesticated from a relatively large number of females, but few males [4]. McGivney et al. reported that centuries of selection for favourable athletic traits among Thoroughbreds acts on genes with functions in behavior, musculoskeletal conformation and metabolism [5]. Recently, some genomic regions were identified as a candidate region influencing racing performance in racehorses [6]. Many researchers applied statistical models to evaluate various parameters on racing performance in Thoroughbred horses [7]. Martin, Strand and Kearney reported that the most influential parameter was distance raced [8]. Cheetham et al. investigated whether both race earnings and number of race starts were associated with horse signalment (age, sex and breed), gait and race surface [9]. Wells, Randle and

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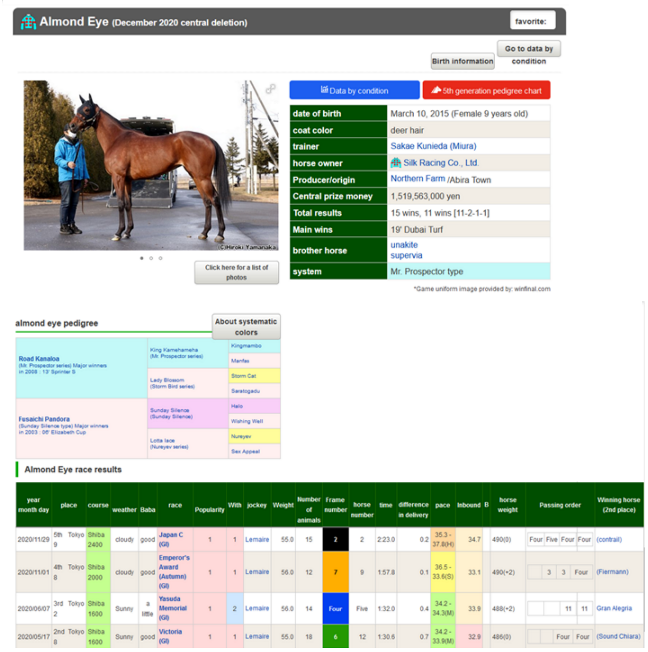

Fig. 1. An example of horse information provided by Keiba Lab.

Williams investigated how temporal, behavior and loading related factors associated with the period before the start of the race influences racehorse performance [10]. Statistical researches are conducted not only in horse racing but also in other sports, such as baseball. In recent years, statistical researches brought a new batting approach that batters should aim for big fly balls rather than grounders [11]. Kato and Yanai reported that Shohei Otani, the Japanese superstar slugger in Major League Baseball (MLB), always aims for hitting fly balls [12]. This new batting approach, the so-called “fly-ball revolution”, shows that even experts may make poor decisions. It is important to discuss how and why experts made poor decisions. Yerkes and Dodson studied the relationship between arousal and performance and showed that a little stress can help we perform a task, however, too much stress degrades our performance [13]. However, experts have a wealth of knowledge and experience, and usually have staff to share their stresses and consider issues with them. Shappell and Wiegmann focused on preventing errors in aviation, including decision errors, and propose a framework for analyzing and classifying human errors [14]. Kang and Yoon studied the types of errors that both younger and older adults make when learning how to use new technologies [15]. They found that older adults used different strategies than younger adults. However, they did not report how experts made poor decisions. Bechara et al. reported we notice danger first [16]. However, they did not study how and why we miss out on opportunities.

III. A COLLECTION OF RACEHORSE INFORMATION

Keiba Lab [17] is one of the most popular horse racing information sites in Japan. This site records various information about all racehorses registered with Japan Racing Association (JRA) and registered users can freely access it. Figure 1 shows an example of horse information provided by Keiba Lab. As shown in Figure 1, the horse information provided by Keiba Lab consists of personal information and race results. Personal data consists of name, date of birth, age, sex, coat color, breeder, birth place, owner, trainer, ancestors up to three generations ago, sire line, career statistics, career prize money, and so on. Race results consist of venue, event date, distance, weather, racetrack, surface, race name, favourite, order of finish, jockey, weight, horse number, frame number, time, and so on. In order to discuss whether even horse racing experts make poor decisions, we collected information about 36869 horses registered with JRA from 2010 to 2017 from Keiba Lab. Table I shows the number of horses registered with JRA from 2010 to 2017.

TABLE I
THE NUMBER OF HORSES REGISTERED WITH JRA FROM 2010 TO 2017

year	number of registered horses
2010	4470
2011	4524
2012	4505
2013	4595
2014	4649
2015	4663
2016	4730
2017	4733
Total	36869

On Keiba Lab, various sire lines are used to classify horses. We surveyed how racehorse sire lines diverged and grouped them into Native Dancer Line, Nearctic Line, Royal Charger Line, and others. For example, Figure 1 shows that the sire line of *Almond Eye* was Mr. Prospector Line. It branched out from Native Dancer Line. As a result, in this study, we determined that the sire line of *Almond Eye* was Native Dancer Line. Then, we classified 36869 horses registered with JRA from 2010 to 2017 into these four types. Table II shows the number of horses classified into these four sire line types. As shown in Table II, 90 percent of the 36869 horses were classified into the three main sire lines: Native Dancer Line, Nearctic Line, and Royal Charger Line.

TABLE II
THE NUMBER OF HORSES CLASSIFIED INTO THE THREE MAIN SIRE LINE TYPES

sire line	number of horses
Native Dancer Line	8777
Nearctic Line	6374
Royal Charger Line	18077
others	3641
Total	36869

36869 horses had competed in races of various distances. We grouped the race distances into five types: 1000 – 1399m, 1400 – 1799m, 1800 – 2199m, 2200 – 2799m, and more than 2800m. Then, we investigated which distance races and how many times the 36869 horses had competed in. For example,

TABLE III
THE NUMBER OF TIMES THE 36869 HORSES OF FOUR SIRE LINES HAD COMPETED IN RACES OF VARIOUS DISTANCES

sire line	race distance 1000-1399m	1400-1799m	1800-2199m	2200-2799m	2800m-	Total
Native Dancer	24264	28895	25762	3474	1767	84162
Nearctic	17228	20917	18728	2589	1240	60702
Royal Charger	38426	62123	65782	11294	4252	181877
others	9328	11228	9979	1672	661	32868
Total	89246	123163	120251	19029	7920	359609

TABLE IV
THE NUMBER OF TIMES THE 36869 HORSES OF FOUR SIRE LINES HAD FINISHED IN FIRST PLACE IN THE RACES OF VARIOUS DISTANCES

sire line	race distance 1000-1399m	1400-1799m	1800-2199m	2200-2799m	2800m-	Total
Native Dancer	1993	2329	2152	348	215	7037
Nearctic	1377	1598	1478	226	154	4833
Royal Charger	2606	4924	5567	1061	545	14703
others	715	866	675	120	74	2450
Total	6691	9717	9872	1755	988	29023

TABLE V
THE NUMBER OF TIMES THE 36869 HORSES OF FOUR SIRE LINES HAD FINISHED IN TOP FIVE PLACE IN THE RACES OF VARIOUS DISTANCES

sire line	race distance 1000-1399m	1400-1799m	1800-2199m	2200-2799m	2800m-	Total
Native Dancer	8691	10322	9783	1498	776	31070
Nearctic	6120	7414	6861	989	513	21897
Royal Charger	12878	22677	25338	4603	1926	67422
others	3127	3854	3368	646	262	11257
Total	30816	44267	45350	7736	3477	131646

Almond Eye had competed in one 1000–1399m race, six 1400–1799m races, four 1800–2199m races, and four 2200 – 2799m races. Table III shows the number of times the 36869 horses of four sire lines had competed in races of various distances.

Horse owners get prize money when their horses place in the top five in races held by JRA. As a result, we investigated which distance races and how many times the 36869 horses of four sire lines had placed in the top and the top five in races held by JRA. Tables IV and V show the number of times the 36869 horses of four sire lines had placed in the top and the top five in the races of various distances, respectively.

IV. ANALYSIS OF POOR DECISIONS MADE BY HORSE RACING EXPERTS

From the viewpoint of outcomes, there are two ways horse racing experts make poor decisions on race selection.

- They do not select races that are likely to have good outcomes.
- They select races that are likely to have poor outcomes.

In this section, we investigate whether horse racing experts made poor decisions in both ways or only one way.

A. Basic idea

It is widely recognized that inherited variation in physical and physiological characteristics is responsible for variation in individual aptitude for race distance. Many horse racing experts would agree that if the best race distance of ancestors is known, the offspring's best race distance is most likely to take after them. As a result, we focus on three factors of racehorses:

- sire line,
- race distance, and
- order of finish.

In this section, we first investigate whether horse racing experts entered their horses of certain sire lines into races of certain distances too many times or too few times. The result of this investigation shows which sire line horses the experts thought were more likely to win or lose races of certain distances. Then, we investigate whether horses of certain sire lines won or lost races of certain distances too many times. The result of this investigation shows which sire line horses were more likely to win or lose races of certain distances. Finally, we compare the results of statistical analyses on experts' race selection and the race results, and detect cases with large differences.

B. Detection of race distance and sire line combinations that horse racing experts selected too many times or too few times

In order to detect cases where horse racing experts entered their horses of certain sire lines into races of certain distances too many times or too few times, we conduct the statistical analysis on the 36869 race horses registered with JRA from 2010 to 2017 by using Hypothesis *ES*.

Hypothesis *ES* If experts did not enter too many times or too few times their racehorses of certain sire lines into races of certain distances, we would expect that experts entered their horses of sire line s_i into races of distance d_j at most $N_{ES}(s_i, d_j)$ times

$$N_{ES}(s_i, d_j) = P_{ES}(d_j) \times \sum_j N_{entry}(s_i, d_j) \qquad (1)$$

where d_j is the type of race distance. We classified race distances into five types:

d_1 1000 – 1399m
d_2 1400 – 1799m
d_3 1800 – 2199m
d_4 2200 – 2799m
d_5 2800m –

$N_{entry}(s_i, d_j)$ is the number of times horses of sire line s_i were entered into races of distance d_j, as a result, $\sum_j N_{entry}(s_i, d_j)$ is the total number of times horses of sire line s_i were entered into races. $P_{ES}(d_j)$ is the probability that an expert enters his/her horse into a race of distance d_j. $P_{ES}(d_j)$ is

$$P_{ES}(d_j) = \frac{\sum_i N_{entry}(s_i, d_j)}{\sum_i \sum_j N_{entry}(s_i, d_j)} \qquad (2)$$

TABLE VI
THE P-VALUES OF EXPERTS' SELECTIONS FOR EACH COMBINATION OF SIRE LINE AND DISTANCE

sire line	race distance				
	1000–1399m	1400–1799m	1800–2199m	2200–2799m	2800m–
Native Dancer	1.0000	0.6938	0.0000	0.0000	0.0209
Nearctic	1.0000	0.8605	0.0000	0.0000	0.0035
Royal Charger	0.0000	0.2035	1.0000	1.0000	0.9999

TABLE VII
THE P-VALUES OF RACE RESULTS (FIRST PLACE) FOR EACH COMBINATION OF SIRE LINE AND DISTANCE

sire line	race distance				
	1000–1399m	1400–1799m	1800–2199m	2200–2799m	2800m–
Native Dancer	0.9999	0.8565	0.7970	0.9426	0.3643
Nearctic	0.9925	0.0917	0.0575	0.2029	0.4978
Royal Charger	0.0000	0.6305	0.9906	0.7313	0.7442

TABLE VIII
THE P-VALUES OF RACE RESULTS (WITHIN FIFTH PLACE) FOR EACH COMBINATION OF SIRE LINE AND DISTANCE

sire line	race distance				
	1000–1399m	1400–1799m	1800–2199m	2200–2799m	2800m–
Native Dancer	0.9999	0.2281	0.8154	0.9989	0.5149
Nearctic	0.9972	0.0708	0.0012	0.0073	0.0383
Royal Charger	0.0000	0.9984	0.9999	0.6604	0.9676

where $\sum_i N_{entry}(s_i, d_j)$ is the total number of times horses were entered into races of distance d_j and $\sum_i \sum_j N_{entry}(s_i, d_j)$ is the total number of times horses were entered into races.

If this hypothesis is rejected by an two-sided binomial test [18], we determine that experts entered their horses of sire lines s_i into races of distance d_j too many times or too few times.

C. Detection of race distance and sire line combinations that gave good or poor results for racehorse experts too many times

In order to detect cases where horses of certain sire lines won or lost races of certain distances too many times, we conduct the statistical analysis on the 36869 race horses registered with JRA from 2010 to 2017 by using Hypothesis *RR*.

Hypothesis *RR* If horses of certain sire lines did not perform well too many times or too few times in races of certain distances, we would expect that horses of sire line s_i finished within $rank$-th place in races of distance d_j at most $N_{RR}(s_i, d_j, rank)$ times

$$N_{RR}(s_i, d_j, rank) = P_{RR}(d_j, rank) \times N_{entry}(s_i, d_j) \quad (3)$$

where d_j is the type of race distance. We classified race distances into five types in the same way that we did in Hypothesis *ES*. $N_{entry}(s_i, d_j)$ is the number of times horses of sire line s_i were entered into races of distance d_j. $P_{RR}(d_j, rank)$ is the probability that a horse finished within $rank$-th place in a race of distance d_j. $P_{RR}(d_j, rank)$ is

$$P_{RR}(d_j, rank) = \frac{\sum_i N_{result}(s_i, d_j, rank)}{\sum_i N_{entry}(s_i, d_j)} \quad (4)$$

where $N_{result}(s_i, d_j, rank)$ is the number of times horses of sire line s_i finished within $rank$-th place in races of distance d_j. As a result, $\sum_i N_{result}(s_i, d_j, rank)$ is the total number of times horses finished within $rank$-th place in races of distance d_j. Furthermore, $\sum_i N_{entry}(s_i, d_j)$ is the total number of times horses were entered into races of distance d_j.

If this hypothesis is rejected by an two-sided binomial test, we determine that horses of sire line s_i finished too many times or too few times within $rank$-th place in races of distance d_j.

D. Results of the investigation

In order to detect racehorse experts' poor decisions, we apply Hypothesis ES and RR tests on the 36869 horses registered with JRA from 2010 to 2017, as shown in Table I. The significance levels for both Hypothesis ES and RR were 0.05. First, we calculated the p-values of experts' selections and the race results by applying Hypothesis ES and RR, respectively. Table VI shows the p-values of experts' selections for each combination of sire line and distance. Tables VII and VIII show the p-values of race results (first place and within fifth place) for each combination of sire line and distance, respectively. Figures 2 and 3 show the p-values of experts' selections vs the race results (first place and within fifth place) for each combination of sire line and distance, respectively.

We applied Hypothesis ES on the 15 combinations of sire lines and race distances and detected

- five combinations the p-values of which were more than 0.975. As a result, experts selected these five combinations of sire lines and race distances too many times. In other words, they strongly thought these five combinations were favorable to win horse races.
- seven combinations the p-values of which were less than 0.025. As a result, experts selected these seven combinations of sire lines and race distances too few times. In other words, they strongly thought these seven combinations were unfavorable to win horse races.

We focused on these twelve combinations that experts strongly thought were favorable or unfavorable to win horse races. Focusing on the difference between the p-values of experts' selections and the race results, we classified these twelve combinations into three types:

- eight combinations where the differences were small. These combinations were plotted at the upper right or the lower left of the graphs in Figures 2 and 3.
- two combinations where the differences were large. These combinations were plotted at the upper left or the lower

right of the graphs in Figures 2 and 3.

- two other combinations.

We focused on the second type: two combinations where the differences between the p-values of experts' selections and the race results were large. This is because there were a sharp conflict between the experts' selections and the race results. In other words, these selections were poor decisions. These two combinations were

- Native Dancer Line (1800–2199m)
- Native Dancer Line (2200–2799m)

It is noteworthy that these combinations were plotted at the upper left, not the lower right, of the graphs in Figures 2 and 3. Especially, the latter case, Native Dancer Line (2200–2799m), was rejected by Hypothesis RR. As a result, in both cases,

- experts selected these two combinations too few times and thought these two combinations were unfavorable to win horse races.
- the race results showed these two combinations were favorable to win horse races.

As mentioned, there are two ways horse racing experts make poor decisions on race selections:

- They do not select races that are likely to have good outcomes.
- They select races that are likely to have poor outcomes.

Both Native Dancer Line (1800–2199m) and Native Dancer Line (2200–2799m) were classified into the former case. The results showed that experts made frequently their poor decisions by not selecting races that are likely to have good outcomes, not by selecting races that are likely to have poor outcomes. We think this is because people are more sensitive to risks than opportunities. In other words, when people lose at something they thought they could win, they carefully consider the consequences. However, when they win something they thought they would lose, they, even experts, do not carefully consider the consequences. Even for experts, it is difficult to update knowledge and experience using good results.

V. Conclusion

In this paper, we investigated how and why horse racing experts made poor decisions on race selections. We analyzed sire lines, race distances, and race results of the 36869 horses statistically and showed that horse racing experts made their poor decisions by not selecting races that are likely to have good outcomes, not by selecting races that are likely to have poor outcomes. The result suggested that people are more sensitive to risks than opportunities. To generalize this finding, we intend to analyze race performance data in other countries and compare the results with those obtained in this study.

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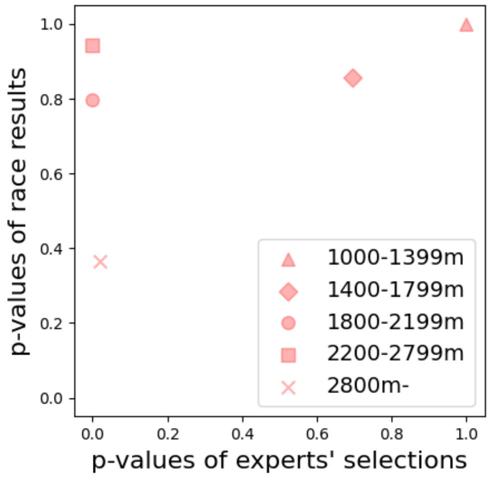
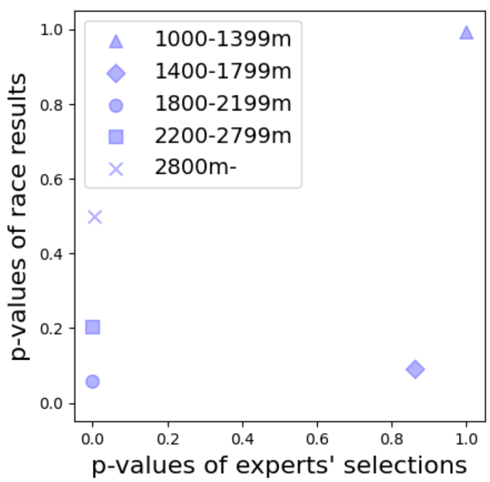
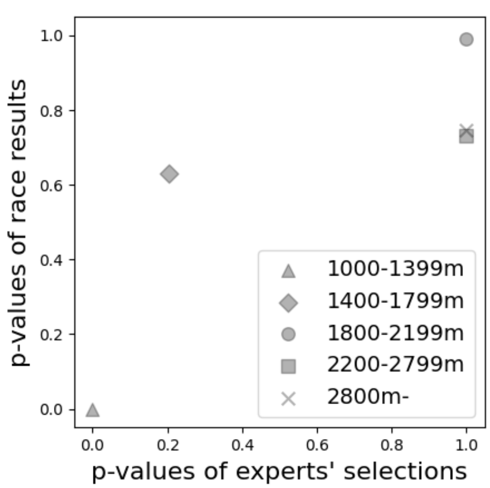


(a) Native Dancer Line

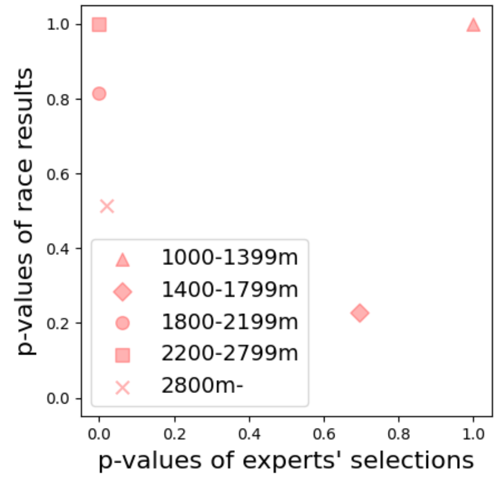


(b) Nearctic Line

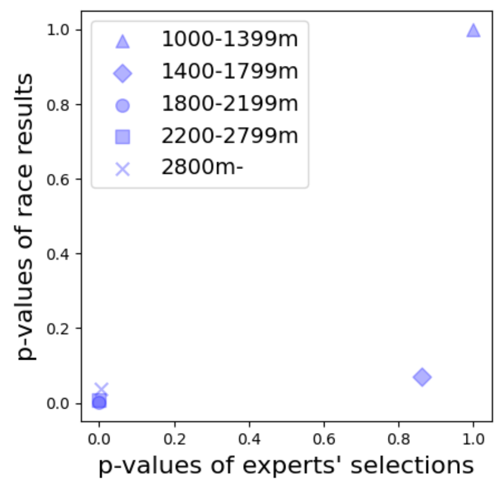


(c) Royal Charger Line

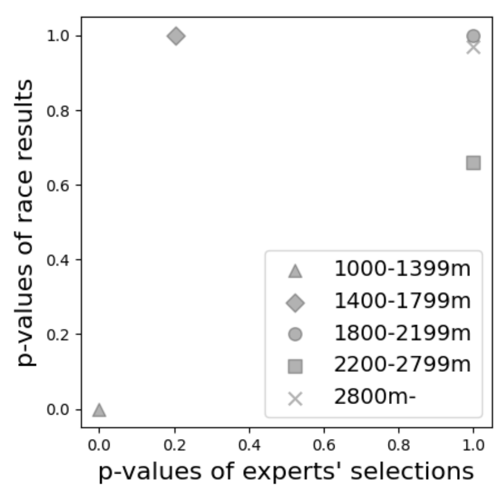
Fig. 2. The p-values of experts' selections vs race results (first place).



(a) Native Dancer Line



(b) Nearctic Line



(c) Royal Charger Line

Fig. 3. The p-values of experts' selections vs race results (within fifth place).

How do Abstraction and Emotions Travel Different Spaces?

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***Abstract*—Emotions *per se* are an intriguing multidisciplinary topic; still, the combination of emotions and technologies brings more layers into the subject. For example, on the one hand, we may consider a socially mediated communication of emotions, and on the other, Artificial Intelligence (AI) systems quickly merging into our realities and spaces. Here, we design an approach aiming to spotlight networked emotions and emotion-driven AI systems. This research started from our goal to encode abstract and emotion-rich contexts into an AI agent modeled after emotions and designed to cooperate purposefully with humans. Here, we narrow our questions to "How do abstraction and emotions travel different spaces?". We present our five-phase project idea to investigate that question, which explores distinct spaces: images, textual descriptions, 3D scenes, and mental models.**

***Keywords-abstraction; emotions; mental models; 3D-scenes*.**

I. Introduction and Motivation

When telling a story, we do not need to provide every single detail; we expect others to fill in the gaps and evoke mental models consistent with the story. For example, if it involves a library, it may be associated with a quiet place filled with books and other associated behaviors/rules. Mental models are "internal representations of the external world consisting of causal beliefs that help individuals deduce what will happen in a particular situation" [1]. We use 'mental models' as an umbrella term that covers spatial mental models and mental representations of environments or 'cognitive collages' [2]. Meanwhile, emotional mental models cover emotions and feelings connected to mental models: "Mental models cause certain expectations/thoughts of how things should look like/work and connect certain emotions with this. Consequently, a mental model is a cognitive and an emotional framework in the brain, influenced by person's personality (genes) and the environment including social variables" [3].

However, what if we wanted to design an AI system capable of making sense of your story? How to encode a combination of abstract contexts and emotions for an AI agent? Would that enable a more holistic contextual evaluation and better-informed decision-making process? We hypothesize that, by investigating abstraction and emotions traveling different spaces, we will gather insights into what abstract and emotion elements are key for a holistic and consistent understanding of emotion-rich contexts. Hence, we investigate the question: *How do abstraction and emotions travel different spaces?* We created a five-phase project (see fig. 1 for an overview) that shares similarities with the telephone game, as a message travels different spaces. Phases are crafted to gather insights into hidden or implicit abstract and emotion elements that help humans interpret emotion-rich contexts holistically. Zheng et al. [4] summarize the work described in [5], helping to describe implicit knowledge: "When knowledge has been articulated, then it is explicit knowledge. Otherwise, another question is raised: Can it be articulated? If the answer is yes, then it is implicit knowledge. If the answer is no, then it is tacit knowledge". Our project Phases are:

• Phase 0, **Image Collection**. Manually collect images whose sense-making requires a holistic approach due to abstract and emotion-rich contexts. We identified the digital space as a good fit to our purposes due to the social nature of emotions and their central place in digital cultures. That led us to images that convey jokes or metaphors characteristic in memes [6]. "The socially mediated communication of emotion is intricately linked to the social textures of networking technologies" [7].

• Phase 1, **Description and Data**. Write raw and detailed image descriptions and categorize the images in a dataset. Feed the Phase 2 team with raw descriptions. Example of a raw description: *A* soaking wet cat sits inside a sink with open eyes that pop out. There is a leading text: "I leave the bathroom shaking cold, and the person asks:" follow-up text: "'Are you cold?' Nope, a ghost is entering me." Unlike detailed, raw descriptions leave details out, which we named "unsaid elements" – Phase 1 team feeds Phase 2 with raw descriptions only, no images, and neither team uses generative AI tools.

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We hypothesize that a) we will uncover hidden relationships across images' concrete and abstract elements as we categorize them, and b) our methods will provide insights into identifying diagnostic images [8] and providing emotion-aware assistive technologies.

• Phase 2, **3D Scenes and Decisions**. Without access to the images, interpret and encode the raw image descriptions into a 3D scene using a tool, such as Blender (see [9] for a review on Blender's versions and interfaces), and document the decision-making process. Unsaid elements can either be on the a) concrete side, e.g., it mentions a cat in a sink but no details about the fur's color or the sink's shape, size, and material/color; or b) more abstract, e.g., 3D modelers may reflect: "this seems to imply discomfort; is it supposed to be humorous?" Hence, 3D modelers have to fill in the gaps and make decisions to build a 3D scene – which we call "assumed elements". Therefore, *unsaid elements* from Phase 1 become *assumed elements* in Phase 2. In fig. 2, we illustrate the 3D modeler's decision-making process (illustration built using the Excalidraw tool [10]).

• Phase 3, **Checkpoint**. Compare: a) raw descriptions and images with 3D scenes and b) unsaid elements with assumed elements and documentation. Examine how/if those differ and what we learned about abstraction/emotions across spaces.

• Phase 4, **App.** Build an application to enable users to interact with our descriptions, dataset, and 3D scenes.

Project Phases and Teams. Each project phase has a dedicated team. A team is composed of people, and excluding Phase 4, they are forbidden to work on more than one project phase. Besides, teams have a strict non-sharing policy: everything a team produces is kept within the team only.

The paper is organized as follows: in Section I, we introduced our project idea; in Section II, we briefly provide background references as we discuss our project. Finally, we conclude in Section III.

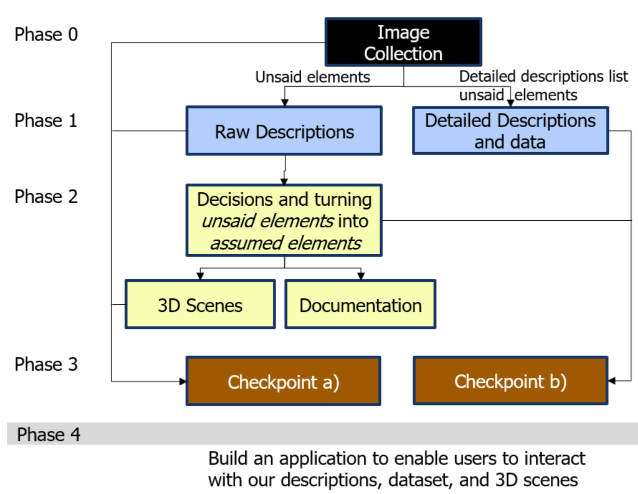

Fig. 1. An overview of the five project phases. For clarity, we omitted the arrows in Phase 4.

II. Background and Discussion

As we started collecting images for Phase 0, two topics became particularly relevant to our research: spatial communication and networked emotions. According to Tversky [11], by using position, form, and movement in space, gestures, and actions convey meanings. In that sense, differently from solely symbolic words, visual communication can directly convey content and structure (both literally and metaphorically). Although it may lack the rigorous definitions words can offer, visual communication delivers flexibility and suggestions for meanings. Such flexibility, in turn, requires context and experience to interpret conveyed meanings [11]. Networked emotions take into account the social nature of emotions and the messy layers of emotion and emotion regulation. It refers to the view of "emotions as multi-layered processes in which intraindividual processes are tightly coupled and often cannot be separated from interindividual processes" [12]. There are many instances where "regulation and elicitation can best be described by nested layers of feedback loops (...) Dealing with nested layers is messy because all layers can potentially influence emotional components" [12]. Finally, it "involves the mobilization of affect in online emotional cultures as a transmittable, spreadable, and self-contained resource, bringing out formerly privately shared emotions into online spaces and collective experience" [7].

As mentioned earlier, our project holds similarities with the telephone game. However, unlike the game, we are setting metrics to ensure objectivity without cutting off open-endedness. E.g., keeping consistent terminologies and processes across phases; building gateways for checking what unsaid elements tend to be correctly assumed by the Phase 2 team and which are not (by "correct," we mean objectively matchable with the original image); besides described concrete elements are easy to check across spaces. In short, the Phase 1 team examines Phase 0 images and produces raw textual image descriptions for the Phase 2 team, responsible for turning descriptions into 3D scenes. A comparison between *unsaid/assumed* elements and teams' documentation will help us investigate how abstraction and emotions travel through spaces. Interestingly, as Phases 0-2 start to shape, we notice a shift in our research questions from AI towards sense-making and networked emotions, and our applications moving to assistive technologies. We hypothesize that the mapping (unsaid/assumed elements) will help to better understand people's emotional mental models, and inform the development of emotion-aware AI systems and assistive technologies.

Our team members across phases engage in sense-making tasks which are, using Pirolli's and Card's [13] words: "information gathering, re-representation of the information in a schema that aids analysis, the development of insight through the manipulation of this representation, and the creation of some knowledge product or direct action based on the insight. In a formula Information → Schema → Insight → Product" [13]; and the re-representation may be in the team's mental models, written or drawn, or digitally represented.

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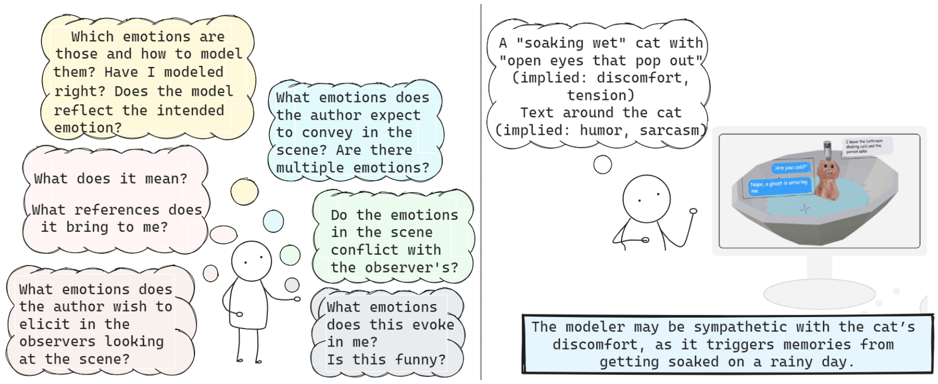

Fig. 2. Left. Challenges 3D modelers may face while dealing with multiple emotional-mental models. Although those are situated in the modeler's thoughts, they represent distinct players: modeler, 3D model, observer (or audience), description, and image's author). The figure illustrates 'layers' or dimensions of emotional processing involved in the decision-making and 3D modeling processes. Right. A modeler making decisions and designing a 3D scene.

Llorens-Gámez et al. [14] show that components, such as form and geometry, space distribution and context, color and texture, among others, influence memory and/or attention, and can be assessed objectively. It will be interesting to investigate, in Phase 2, to what extent familiar shapes or contexts populate a 3D modeler's assumed elements. If a modeler is used to seeing wood-made and square-like sinks, are those going to occupy matching assumed elements? (Of course, there are other players, such as how easy it is to design that shape and texture.) Or if an emotional context is related to disgust in the modeler's culture but anger in the original image's culture, will the 3D scene still be consistent with the original image? Images that are meant to be humorous to some may not be to others because humor shifts in different cultural contexts (see [15] for a view on how cultures create emotions). Modelers engage with networked emotions and emotional-mental models as they switch between and across mental models to guide the sense-making of a new description and decision-making that leads to creating a 3D scene. To conclude, this project raises many insightful questions for further investigation. For example, how to treat images that call for a "presupposed participant", images that expand their scope as they incorporate us, outside observers, as if we were part of the image/meaning? Back to AI systems, how to help an AI system to "see itself" as part of a context before producing a context's holistic understanding?

III. Conclusion

Seeking to understand what a holistic understanding of abstract and emotion-rich contexts could look like for an AI system, we created a five-phase project to investigate *how abstraction and emotions travel different spaces*. Given the challenges inherent to the investigation of emotions, we are identifying metrics to ensure objectivity and map how a message travels through spaces. As we do so, questions that are challenging but worth investigating are emerging, and we hypothesize they will bring insights into research in emotions and how to build emotion-aware AI systems and assistive technologies. For example, how informative would it be if an emotion-driven AI system outputted its decision log on emotions in a narrative-like sequence of pictures (or 3D scenes) and text?

Acknowledgments

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