Healthy Lies: The Effects of Misrepresenting Player Health Data on Experience, Behavior, and Performance

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ABSTRACT

Game designers use a variety of techniques that mislead players with the goal of inducing play experience. For example, designers may manipulate data displays of player health—showing they have less health than they actually do—to induce tension. While commonly used, players make decisions based on in-game data displays, raising the question of how misrepresentations impact behavior and performance, and whether this might have unintended consequences. To provide a better understanding of how data misrepresentation impacts play, we compare two versions of a game: one that displays health accurately and one that misrepresents health. Our results suggest that even subtle manipulations to data displays can have a measurable effect on behavior and performance, and these changes can help explain differences in experience. We show that data misrepresentations need to be designed carefully to avoid unintended effects. Our work provides new directions for research into the design of misrepresentation in games.

CCS CONCEPTS

• **Human-centered computing → User interface design**; *Information visualization.*

KEYWORDS

Game design, player experience, health bars, data misrepresentation, deception

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1 INTRODUCTION

Modern video games often include many data displays that help communicate important information about the state of the game (e.g., time, progress or score) and the state of the player (e.g., identity, health, experience or abilities). Players make use of data displays in order to make decisions about what actions to take and what strategies to employ. Game designers must carefully design how data displays communicate game data to ensure that they are usable, while aligning seamlessly with play mechanics, game theme, and story [20].

Data displays can also be a tool that designers use to support a particular play experience. Importantly, game designers do not only decide on what information to show, but exactly how to show it. Game designers sometimes change how data is typically displayed to induce a particular experience. For example, the health bar in Assassin's Creed (Ubisoft 2007) loses health quickly when players are closer to full health, and more slowly when a player has low health [29]—a manipulation that would have the effect of players interpreting their current situation as being more precarious than it actually is, raising the pressure and tension they feel.

Manipulating a data display, like the one in Assassin's Creed, could have three main effects on players. First, as described above, play experience might be affected. Second, player behavior might change; since players use data displays to make decisions about what they do in the game, it seems likely that manipulating important data will also change what actions players take. Third, player performance might be affected; if players change their actions in games, these might lead to changes in performance (e.g., scoring more or less) and outcomes (e.g., winning more or less) in the game. Further, it is likely that changes in behavior and performance would change the experience that players have, in addition to the displays themselves influencing experience. While game designers are likely aware that manipulating data displays to induce play experience can have side effects on behavior and performance, exactly how such manipulations can and do affect behavior, performance and play experience has not been well studied.

While there exist many potential data misrepresentations that could be studied within games, we focus on the health bar for two main reasons. First, players have a basic mental model about how health bars work: *the amount of the bar that is filled represents how much health I have.* Second, there are real world examples of health bar manipulations in commercial games, but there is little information about how they impact game play.

In this work we provide a first study to explore how subtle manipulations on a common data display can have substantial and significant effects on player experience, behavior and performance. 125 participants played one of two versions of a game—the two versions of the game varied only in how health values were mapped to the health bar. The first version represents a typical health bar that follows a typical mapping, where the amount of the health bar filled corresponds directly to the amount of health the player has. The second version provided an experience enhancing mapping—similar to Assassin's Creed—that displays a greater loss of health when a player is near full health and a smaller loss of health when the player is at lower health.

Our work provides the following six contributions:

1. We provide a first systematic study of the use of misrepresentation in game-based data displays.
2. We show that even subtle manipulations of data displays have a measurable impact on player experience, player behavior, and player performance.
3. We describe what aspects of play experience data misrepresentations affect (tension and competence) and do not affect (enjoyment and experience of working hard).
4. We identify new ways that game designers can employ data misrepresentation (to balance play experience) and the potential implications for its use.
5. We provide a new and freely available game system that can be used as a testbed for future work in health mechanics and manipulation of data displays.
6. We identify new directions for research in both data misrepresentation and health mechanics.

2 RELATED WORK

Game Design and Play Experience

Many games can be viewed as a "series of interesting decisions", where the goal of the designer is to carefully balance what and how information is provided to a player (Sid Maier quoted in [3]). When considering the decisions that players must make, designers try to provide a desired play experience by ensuring that a game contains the right amount information to best balance challenge. Game designers, therefore, are interested in providing information that appropriately suits the mechanics, theme and challenge of a game [26]. However, the design of in-game information and data displays is an understudied area of research [35], and little is known about how they might affect play experience.

Assessing Player Experience

Play experience research has developed a number of concepts to help describe and evaluate experience including flow [28], fun [22] and motivation [26]. Because the amount of challenge has an impact on the outcomes of the game, most research has focused on showing how player performance predicts game enjoyment [30]. However, measuring play experience is complex as there are many related and complex factors that can affect the experience of challenge in games [12]. For example, recent work has examined how expertise [21], the alignment of skills between competitors [17], the type of controller used [8] and social settings [7] influence player experience. This suggests that continued research into the many factors that contribute to and affect play experience is necessary.

Among the existing instruments in player experience research we describe the Intrinsic Motivation Inventory (IMI) [24], since it is used in our work. IMI measures the constructs of enjoyment (experience of interest/enjoyment), effort (trying hard and being cognitively invested), perceived competence (feeling mastery over a task), and tension (feeling pressure or tension). IMI is commonly used in player experience research via questionnaire [26].

Representing and Misrepresenting Data

Misrepresentation and Deception in HCI. Recently, Adar et al. explored the use of "benevolent deception" in HCI [1]. They describe deception as the intentional mismatch between a person's perception of a system and the actual system state (e.g., a progress bar that shows 90% complete when it is not the case). This can be achieved via "... an explicit or implicit claim, omission of information, or system action." Distinguishing between malevolent deception (e.g., tricking people into performing an undesirable action) from altruistic deception (i.e., deception that improves user experience), they highlight that in any situation where there is a mismatch between a person's desire (e.g., their expectations) and reality (e.g., skill required to complete an action) there is an opportunity to use deception.

Manipulating Gameplay to Influence Play Experience. Games have a long history of manipulating gameplay to influence experience. For example, in the Mario Kart series (Nintendo) it is well known that the chance of receiving power-ups is dependent on position in the race; trailing players receive the most helpful items, while players in front receive the least helpful. Techniques like this are referred to as dynamic difficulty adjustment, which aim to align player skill with game challenge [4, 5, 27]. However, game designers have employed other heuristics to help relax certain mechanics to provide players with an improved experience. Gears of War 3 (Epic Games 2011) provides players new to the multiplayer mode damage bonuses that are reduced after the first few kills. Far Cry 4 (Ubisoft 2014) reduces NPC (non-player character) accuracy and damage the closer they are to a player, which encourages players to enter close and exciting encounters.

Games researchers have also evaluated several different approaches for improving play experience through manipulating different aspects of gameplay. For example, several projects have looked at various aspects of balancing between players of different skill levels in a range of game genres through subtle assistance [6, 13, 32]. Evaluations of these techniques have shown consistent positive benefits on play experience (e.g., subjective ratings of fun [6, 13]), and that they do not harm other aspects of gameplay such as skill development [18]. Importantly in much of this work, users were unaware that assistance was being used to help or hinder performance in the game. Interestingly, when assistance for player balancing has been disclosed to players it did not harm their experience. Depping et al. [16] used attribution theory to explain this result, highlighting that players tend to take credit for their successes (e.g., "I won because I played well") and blame external factors when they fail (e.g., "The controls are too difficult").

Misrepresentation of Data in Games. Studies that examine the misrepresentation of data to influence experience have been explored less frequently. Recent work has examined the manipulation of player position on leaderboards. Finding that manipulating success increases player perception of competence, autonomy, enjoyment, presence, and positive affect as compared to failure, and the manipulations were not highly detectable by players [12]. Other work demonstrated that describing others on leaderboards as being "a similar player" led players to perform better in the game [14].

Misrepresenting Data and Data Displays in Games. In-game data displays (such as health, mana or experience bars) are often used to provide the player with important information, and as such are an important part of making decisions in games [34].

In general, it is well-understood in information visualization that distortion in data graphics is not desirable [31]. Tufte's well-known concept of the "lie factor" suggest the size of the effect shown in a data display should be directly proportional to the size of the effect in the actual data [31]. As described above, however, game designers often manipulate aspects of game design to provide a desired play experience, suggesting this general guideline is not always followed in the context of games. Indeed, there are several examples where games do not consistently display data with the goals of improving play experience. In both Assassin's Creed (Ubisoft 2007) and Doom (Bethesda Softworks 2016) health is lost more quickly when the health bar is full but lost more slowly when health is low. We hypothesize that this is done to raise the experience of tension in the game. However, no previous work has explored the manipulation of data displays and how it might affect player experience, performance and actions in the game.

Of further interest is that since player experience is often the focus of games research it is important to establish what contributes to it. Because players make decisions based on the information the game provides them with, it is likely that behavior is changed when data misrepresentation is used and that this may lead to a change in performance. Further, it could be that both behavior and performance might help explain any change to experience.

3 STUDY OF HEALTH DATA MANIPULATION

To provide a better understanding about how manipulations to game data can affect player behavior, performance and experience we conducted a between-subject experiment analyzing the play and subjective experience of 125 participants. Participants played one of two versions of the game we built, called *Redline*. The two versions of Redline differed only in how they presented health data. The two types of health bars are: a *typical* health bar that directly maps the character's health to the length of the bar; or, an *experience-enhancing* health bar that subtly manipulates how health data is mapped to the bar in an effort to raise the tension experienced by players.

Apparatus

Redline[1] is a 3D, web-based, voxel-styled, top-down firefighting game developed in Unity 5.6 using WebGL.

Gameplay. In Redline players control a male or female firefighter in-training from a top-down view and navigate around a small home to extinguish flames with water (see Figure 1). The goal of the game is to extinguish all flames on a level before reaching zero health (and needing to be rescued by fellow firefighters) or before the 60-second onscreen timer elapses.

Redline uses standard keyboard and mouse controls. The movement of the avatar is controlled via WASD or arrow keys. The avatar faces in the direction of the mouse pointer

[1] Redline source on Github: https://github.com/hcilab/Redline

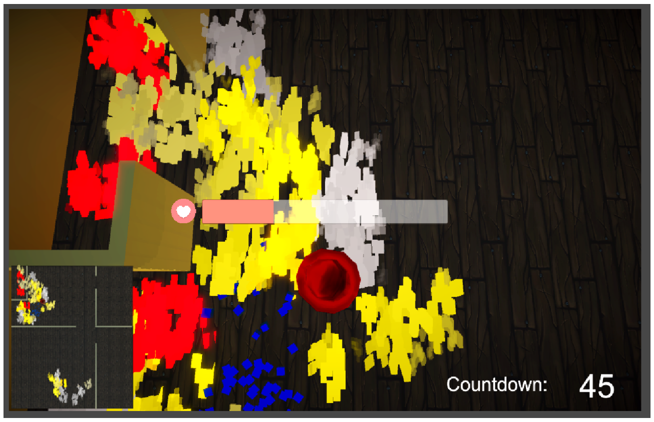

Figure 1: Game play screen of Redline. The firefighter's helmet can be seen spraying blue water. The interface components including the health bar (above the player), the minimap (lower-left corner) and count-down timer (lower-right corner) are shown.

and clicking and holding the left mouse button sprays water in that direction. Water spray has a limited reach.

Strategy. Each level varies in the placement, number, and intensity of flames (see Figure 1). Flames grow over time and spread over the map. Flames have four levels of intensity: progressing in both intensity and hue from light gray smoke to yellow flame, orange flame, and dark red flame. Players receive damage when they are within a set distance from the flame, scaling up the closer the avatar is to the flame. The darker the flame the more health they remove. Spraying water on the flames lowers their intensity until they are fully extinguished. However, to extinguish a flame, a player must be close enough to it. The closer they are the faster they are able to put out a fire, but the more health they will lose.

The distance needed to hit a flame with water is the same distance at which the player takes damage. This, together with the 60-second timer and mechanic that spreads fire, provides a time pressure on players to act quickly, but to not be overly assertive to put themselves in danger.

Players, therefore, must constantly be working to strike a balance between extinguishing as many of the darker flames as possible, while maintaining a safe position (i.e., extinguishing the fast spreading flames as quickly as possible, while minimizing the amount of health lost). If players are overly assertive they will lose too much health and not be able to put out all the flames. If players are not assertive enough they will not be able to extinguish the flames before the timer elapses. An optimal strategy is one that minimizes health loss and the spread of the flames.

Health Bar Display. Health is monitored by a large health bar displayed over the avatar. Health is mapped in one of two ways, as described in more detail below (see Figure 4). When health is full the bar is green and transitions to red as the bar approaches empty. To provide reinforcement when the avatar loses health, the health bar shakes to make the loss more visually salient. When starting a level players start with a total of 1000 health points.

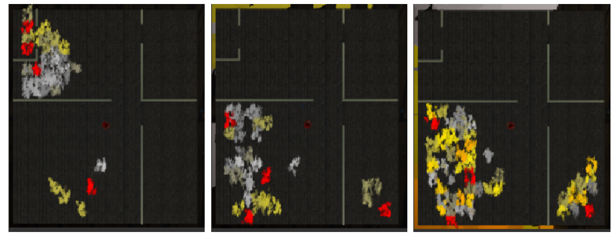

Figure 2: Maps demonstrating different levels and game states. Left: Testing level 1 at the beginning of the level; Center: Testing level 2 at the beginning of the level; Right: Testing level 2 after the flames spread without player action for 20 secs.

Health Bar Versions. Our game has two versions of the health bar, that are presented in two otherwise identical versions of the game. The two health bar versions are a linear, *typical* health bar and an *experience enhancing* bar. The typical health bar provides a direct mapping between health remaining and the size of the bar (e.g., when at 75% health remaining, the bar is 75% full). The experience enhancing bar provides a subtle manipulation of how health data is mapped to the bar, initially exaggerating health loss when the player has full health and gradually slowing the health loss as the bar approaches zero (Figure 4). We call this an "experience enhancing" bar because we were inspired by games that manipulate data to create a target game experience.

With our experience enhancing bar we aimed to raise the amount of tension experienced by players, since this bar shows lower health throughout the game, making it feel extra challenging and situations more serious than they would with the typical bar. We wanted the health manipulations created by the experience enhancing bar to be subtle so that they would not be easily perceived by players, allowing us to evaluate how small manipulations impact play.

Through play testing and piloting, we established the following formula for mapping health data to the length of the bar displayed for the experience enhancing bar:

$$L_n = \frac{(f(n)-1)\times\frac{f(n)+2}{2}}{(\rho-1)\times\frac{\rho+2}{2}} \tag{1}$$

Where L is the length of the bar, and n is the percentage of health remaining. We then defined $f(n) = n \times 10 + 1$ and $\rho = 11$ so that $L_{0\%} = 0\%$ and $L_{100\%} = 100\%$. Figure 3 and Figure 4 display differences between the Typical Health Bar and

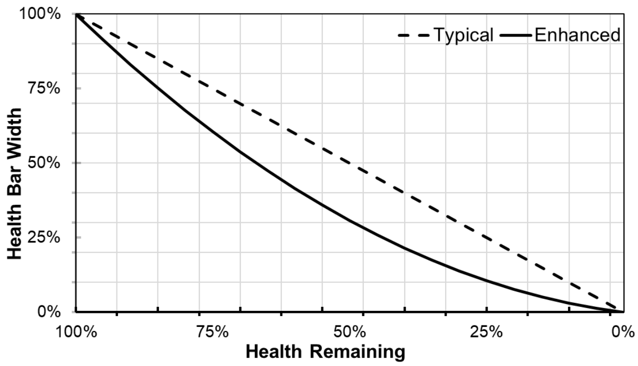

Figure 3: Line chart displaying the correspondence of Health Remaining in percentage (x-axis) to Health Bar Width in percentage (y-axis), split by Typical Health Bar (stitched line) and Typical Health Bar (continues line).

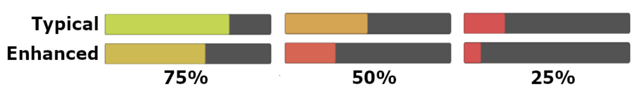

Figure 4: Mock-up of Health Remaining mapped to Health Bar Width of the Typical Health Bar (top) and the Experience Enhanced Health bar (bottom) at 75%, 50%, and 25% health.

the Experience Enhanced Health bar (the latter results from Formula 1).

Levels. In our experimental system we designed two sets of levels. The first set, the tutorial, consisted of 7 levels that progress in challenge, allowing players to get comfortable with the game controls. For example, the first tutorial level required a player to extinguish a small fire that appeared directly in front of them. By the seventh tutorial level, players must extinguish two small fires in separate rooms.

The second set of levels, the testing levels, consisted of 4 levels that were substantially more difficult than the tutorial levels. These levels were designed to require players to monitor their health closely to make effective decisions. All four levels started with two large fires that varied only in their positioning around the game map. Through playtesting we found this approach allowed some degree of control, but that the levels played quite differently.

To provide reinforcement on the outcome of levels, a simple level summary screen is displayed after each level. When players are successful they are rewarded with a congratulatory message (e.g., "Way to go!"), and when they fail they are provided with a message that highlights their failure in a playful way while providing encouragement (e.g., Upon running out of health the following message is provided: "Get out of there, you are going to get hurt! Keep trying!"). Whether a player is successful or not, the game progresses to the next level.

Study Participants and Deployment

In our study we report on the analysis of 125 participants who we recruited from Amazon Mechanical Turk. A total of 179 US-based, adult participants from Amazon Mechanical Turk (MTurk) completed our study. We removed 31% before analysis for the following reason: (1) We set minimum computer hardware requirements (e.g., CPU speed and memory) on our "Human Intelligence Task" (HIT), which we determined through testing our game on various platforms. However, during initial analysis we determined that many participants likely experienced poor performance in the game, despite completing the study, which was determined by logging the frames-per-second (FPS) throughout the study. (2) To ensure that a minimal level of playability was met, we initially removed 47 participants from analysis, who had successfully completed the study, but who did not have at least 60% of their gameplay at a framerate of 15 FPS. We eliminated 2 participants that did not meet the following criteria: they filled in more than 2 surveys with zero variance between items or showed ratings of $\pm 3SD$ in more than 2 questionnaires. (3) We eliminated 5 participants who only produced questionnaire responses but no game play data. This resulted in 62 participants who used the typical health bar, and 63 who used the experience enhancing health bar.

Demographics of the 125 participants included for analysis were as follows: gender (36.8% female, 0.8% other), age (M=33.91, SD=8.04), highest education completed (46% bachelor's or higher, 36.8% some college or associate degree, 16.8% high school diploma), ethnicity (77.6% white, 8% asian, 7.2% black, 4.8% hispanic/latino), and marital status (7% divorced/separated, 38% married or domestic partnership, 55% single and never married).

Procedure

Upon accepting the HIT (the MTurk task), participants accessed a website that guided them through the study. The website initially assigned participants into one of the two between-subject conditions. Participants were first presented an informed consent form, followed by a demographic questionnaire, and then given a brief tutorial that introduced the game through a series of annotated still shots (including the story, goal, controls, and how information is displayed—e.g., timer and health bar). Finally, players completed two gameplay sessions, which were each followed by play experience questionnaires. A final exit questionnaire was administered after all gameplay sessions, and participants were provided a completion code that they submitted to receive payment of $5 USD. The entire experiment required approximately 30 minutes to complete.

We organized our experiment around two game play sessions. The first was arranged to get players up to basic competency with the game, while the second aimed to have them to recognize the need for a strategy to be successful. The first of the two gameplay sessions required participants to play the 7 tutorial levels and the first two of the four testing levels. Upon completion of play session one, players completed the play experience questionnaires for the first time. The second gameplay session followed, which consisted of playing all four levels of the testing set twice (8 levels in all). Through playtesting we had established that playing the testing levels multiple times was important to allow players to learn the strategies, get accustomed to the controls, and recognize the importance of monitoring the game data (health and time). The goal was to get players to a basic level of competency for the final four testing levels of the experiment.

Performance, Behavior, and Experience Measures

In-game metrics were used to measure performance and behavior, while questionnaire data was used to assess experience.

Performance. To assess performance, we collected *health* at the completion of each level, *win rate*—how often the player extinguished all fires on each level, *timeout rate*—how often the player ran out time before extinguishing all fires, and *death* rate—how often the player ran out of health before all fires were extinguished. In our experience developing and playing Readline, we felt that health is a strong indicator of how effective players are at the game. Players with a better strategy will lose less health because they are able to attack flames without putting themselves in a dangerous position. In our initial analysis we observed that death rate and win rate are highly negatively correlated (r=-.75). Therefore, we omitted win rate from all further analysis.

Behavior. To assess the constant balance players made between moving towards a fire to extinguish it and preserving health, we collected the following measures every second of the game: *health lost*—the count of health points lost—and the number of fires in the character's *proximity*—counted as the fires that damage the player (min.=0, max.=25 fires). Higher levels of proximity and health loss would indicate more assertive behavior; i.e., players would expose themselves to a high number of fires in an effort to extinguish more fires, faster. Therefore, we present health loss and proximity as indicator variables of assertive play.

Player Experience. We used a validated scale to assess experience and deployed a series of questions regarding the usability and utility of the health bars.

We measured intrinsic motivation using the Intrinsic Motivation Inventory (IMI, [24]). The IMI measures the agreement to 18-items using a 7-point Likert scale. The instrument measures the following four constructs: *enjoyment*—"I enjoyed this game very much"; *effort*—"I put a lot of effort into this game"; *competence*—" I am pretty skilled at the game"; *tension*—"I felt tense playing the game".

To assess the usability and utility of both health bars, we presented participants with seven items (see Table 1) after the experiment was completed. Participants rated their agreement for each item using a 7-point Likert scale.

Analysis

All data was analyzed using SPSS 25 and Hayes' PROCESS-macro for SPSS (see [11] for details).

The Kolmogorov-Smirnov test for our health bar items suggested non-normal distributions (p<0.01 for all items). Therefore, we used Mann-Whitney U tests for independent samples to analyze the health bar items.

To determine the strength of relationships between variables we used regression analysis. To investigate the effect of health bar manipulation on performance and experience, we performed ANCOVAs with age and gender entered as covariates. We decided to control for age and gender, because both variables have shown effects on play performance before [9, 33].

To investigate the effect of health bar manipulation on the relationship between performance and experience we used moderation analysis; see Hayes for a detailed description of moderation analysis [19].

Because level completion time varies widely (M=41.13, SD=14.12) as a result of skill, strategy, and outcome (i.e., timeout, win, loss) we initially sought a way to compare play regardless of time spent in a level. To account for temporal difference between participants, we divided each level into one of ten temporal bins—averaging values for a metric (i.e., proximity and health loss) per bin. This resulted in 10 bins for each level (bin 1=1-10% of the level completed, bin 2 = 11-20%, ..., bin 10 = 91-100%). We investigated the effect of health bar manipulation on behavior using a mixed ANOVA with health bar condition entered as a between subject factor and temporal bin as the within-subject factor, for proximity and health lost.

Descriptive statistics for performance measures (i.e., health, win-rate, loss-rate, and timeout rate), the average scores for all four IMI constructs, the individual performance measures (i.e., proximity and health), and aggression metrics (health lost and proximity) by bin can be found in Table 3.

Considering that partial η^2 as reported by SPSS overestimates effect sizes [23], we additionally provide ω^2 [2].

4 RESULTS

Below we present the results of our analyses organized by our main research questions. We further describe the specific statistical methods used where appropriate.

Did participants realize that the health bar was manipulated or use the health bars differently?

Participants seemed to be engaged in gameplay throughout the study. Our analysis showed that all participants moved their characters throughout play, and they required a mean of 8.6 minutes (*SD*=2.6) to complete the gameplay sessions; meaning they did not take breaks between levels and were uniform in their gameplay.

We were mainly interested in how health bars were perceived by our participants. Obvious differences between both health bars would defy our intention to create a subtle manipulation with the aim to alter play experience. Our results suggest that there is no noticeable difference between the bars—see Table 1 for descriptive statistics and Mann-Whitney U test results.

Participants were only told that we were assessing player experience in a game, and when asked to describe what the purpose of the experiment was only 2/125 participants mentioned the health bars.

	Typical	Enhanced	
	M *(SD)*	M *(SD)*	p
1. The health bar helped me achieve my goal in the game	4.76 *(1.89)*	4.68 *(1.63)*	.504
2. The health bar helped me be effective in playing the game	5 *(1.77)*	4.67 *(1.73)*	.215
3. I was aware of my health levels while I was playing	6.4 *(.86)*	6.05 *(1.28)*	.074
4. I found the color of the health bar more useful than it's fullness	3.15 *(1.73)*	3.40 *(1.88)*	.527
5. I found the health bar confusing	1.92 *(1.49)*	1.79 *(1.19)*	.819
6. I found the health bar distracting	2.55 *(1.99)*	2.78 *(1.84)*	.257
7. I did not notice the health bar	1.44 *(.92)*	1.52 *(.759)*	.251

Table 1: Mean and standard deviation by health bar item and p-values from Mann-Whitney U tests for independent samples.

	Typical		Enhanced	
	M	*SD*	*M*	*SD*
Performance				
Victory	0.51	0.42	0.46	0.43
Death	0.33	0.34	0.32	0.38
Time-out	0.17	0.23	0.22	0.33
Health Points	628.75	68.76	663.55	71.08
Behaviour				
Proximity	2.11	0.40	2.16	0.90
Health loss	24.08	4.86	24.56	11.11
Experience				
Enjoyment	4.94	1.52	4.55	1.47
Effort	5.94	1.31	5.86	0.90
Competence	5.17	1.93	4.59	1.84
Tension	3.37	1.81	4.02	1.54

Table 2: Descriptive statistics for performance, behavior, and experience by health bar condition.

Does health bar manipulation alter experience and/or performance?

Table 2 provides a summary of descriptive statistics for performance, behavior and experience by health bar condition.

Performing individual ANCOVAs on the experience measures controlling for age and gender, our results show higher levels of competence in the typical health bar condition (M=5.17) compared to the experience enhancing health bar condition (M=4.55), $F_{1,123}$=4.59, p<.05, η_p^2=.037, ω^2=.028. Experienced tension is decreased in the typical health bar condition (M=3.37) compared to the experience enhancing bar condition (M=4.02), $F_{1,123}$=4.991, p<.05, η_p^2=.04, ω^2=.024. There were no significant differences for enjoyment (p=.17) or invested effort (p=.80).

Investigating performance data using ANCOVAs we entered age and gender as covariates, our results show that participants in the typical health condition have less health on average (M=628.75) compared to the experience enhancing health bar condition (M=663.54), $F_{1,121}$=7.758, p<.01, η_p^2=.06, ω^2=.052. There were no differences in the outcome for the performance rate (death rate: p=.793; timeout rate: p=.287).

Taken together, these results show that subtle manipulations of in-game data affect experience (i.e., competence, and tension) and performance (i.e., health). However, the relation between performance and experience remains unexplored.

Does performance predict experience?

To investigate the effect of performance on experience, we performed two separate regression analysis for each experience variable (i.e., tension and competence) as the outcome variable and the three performance measures (i.e., death rate, timeout rate, and health points) as predictors.

Our results show that performance data predicts experience of tension ($F_{3,121}$=3.246, p<.05, R^2=.052). The individual coefficients show that death rate (β=1.19, p<.01) and timeout rate (β=1.05, p<.05) predict tension, while health points do not predict tension in our model (p=.45). Predicting competence by the three performance measures using regression analysis reveals the same pattern, $F_{3,121}$=31.26, p<.001, R^2=.42. The individual coefficients show that death rate (β=3.19, p<.001) and timeout rate (β=2.43, p<.001) predict competence, while health points do not predict experience of competence (p=.884).

Our results confirm that performance affects experience—a result that doesn't necessarily come as a surprise but provides further insights into the exact composition of experience in the context of our study. Specifically, we see that there is a very strong effect of performance on competence (R^2=.42) and a small effect on tension (R^2=.052). It remains, however,

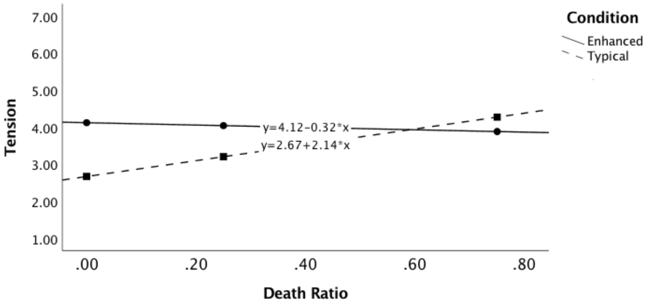

Figure 5: Moderation analysis for the relationship between tension and death rate, moderated by experience condition (typical, enhanced).

unclear how subtle manipulation of displaying health information affects the relationship between performance and experience.

Does the manipulation of health information affect the relationship between performance and experience differently?

We have established that performance predicts experience and that experience and performance can be altered through the manipulation of displaying health. To investigate the effects of health bar manipulation (M) on the relationship between performance (X) and experience (Y), we conducted a moderation analysis (model=1, [19]) controlling for age and gender.

Predicting tension by death rate moderated by health bar manipulation, our results show a significant model (p<.005, R^2=.15), with significant results of condition on tension (p<.05) and a significant interaction between condition and death rate (p<.005). The conditional effects show an increase of tension over death rate for the typical health bar condition (p<.005), but no increase for the experience enhancing condition (p=.59); see Figure 5.

There were no significant moderation effects for health points (p=.36) or timeout rate (p=.56) predicating tension moderated by time, and no significant moderation effects for health points (p=.21), death rate (p=.39), or timeout rate (p=.83) predicating competence moderated by time.

The results suggest that enhancing the experience indeed results in a more stable experience of tension independent of a players' death rate.

Can changes in experience between conditions be explained through differences in behavior?

Because our results indicated that participants were making use of health bars and that these did bring about change in experience and performance, we decided to look at our assertiveness metrics over time. Table 3 shows a summary of the Proximity and Health Lost metrics for each temporal bin and health bar. The number of bins was iteratively decided upon in an attempt to minimize noise.

		Bins									
		1-10%	*11-20%*	*21-30%*	*31-40%*	*41-50%*	*51-60%*	*61-70%*	*71-80%*	*81-90%*	*91-100%*
		Proximity									
Typical	*M*	1.998	2.630	2.731	2.399	2.160	2.118	1.898	2.088	2.032	1.563
	SD	0.814	1.035	1.244	1.121	1.507	0.816	1.107	1.255	1.519	2.405
Enhanced	*M*	1.838	2.521	2.401	2.066	2.387	1.989	2.014	1.972	2.153	2.266
	SD	0.945	1.165	0.968	0.925	0.843	0.796	0.661	1.001	0.857	1.208
		Health Loss									
Typical	*M*	10.927	26.137	28.800	29.050	24.299	24.519	22.143	25.067	27.600	22.300
	SD	6.303	12.117	22.035	13.880	16.229	15.212	17.116	15.683	17.937	38.953
Enhanced	*M*	10.725	22.757	28.883	23.480	27.886	24.258	24.821	25.037	27.358	30.440
	SD	7.732	14.780	14.024	13.409	11.181	10.639	8.487	10.985	14.217	17.425

Table 3: Mean and standard deviation for proximity and health loss by bin and health bar.

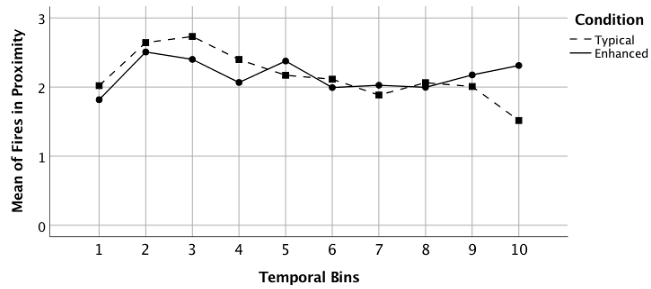

Figure 6: Line chart of the mean of fires in proximity to the player by temporal bin and condition.

A mixed ANOVA with health bar as the between-subject factor and the 10 temporal bins as the within-subject factor revealed that there was no between-subject effect of health bar display on proximity, $F_{1,121}$=0.011, p=.916. However, our analysis showed that proximity varies between temporal bins, $F_{9,1089}$=9.11, p<.001, η_p^2=.07, ω^2=.062. Testing the interaction between the health bar condition and the 10 temporal bins, our results show an interaction effect for proximity, $F_{9,1089}$=3.715, p<.001, η_p^2=.03, ω^2=.022. Bonferroni corrected pairwise comparisons reveal that proximity between health bar conditions differentiates in the 10^{th} bin (p = .008). See Figure 6.

We performed the same mixed ANOVA analysis on the amount of health lost—players start each game with 1000 health points. Health bar was entered as the between-subject factor and the 10 temporal bins as the within-subject factor. Our results reveal that there was no between-subject effect of health bar display on health loss, $F_{1,121}$=0.154, p=.695. However, our analysis showed that health loss varies between temporal bins, $F_{9,1089}$=4.034, p<.001, η_p^2=.03, ω^2=.022. Testing the interaction between the health bar condition and the 10 temporal bins, our results show an interaction effect for proximity, $F_{9,1089}$=2.54, p<.001, η_p^2=.02, ω^2=.021. Bonferroni corrected pairwise comparisons reveal that health lost

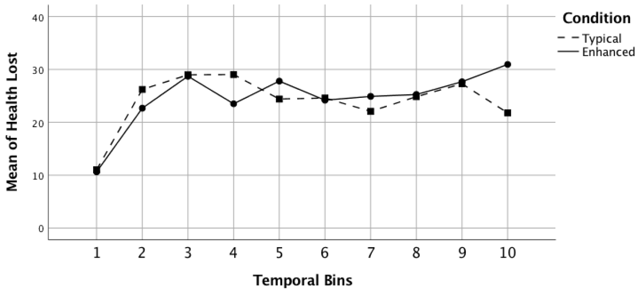

Figure 7: Line chart of mean health loss by temporal bin and condition.

between health bar conditions differentiates in the 4th bin (p=.027). See Figure 7.

Overall, these results must be interpreted carefully since they are far from conclusive. However, taken together the interaction effects suggest that players seemed to be more assertive in the early game with the typical health bar but are more assertive towards the end of levels with the experience enhancing health bar.

Summary of Results

Our analyses lead to the following main findings:

1. *The experience enhancing bar works.* Experience (competence and tension) and performance (amount of health) are affected by our data display manipulation.
2. *Players didn't notice the misrepresentation of health data,* and no differences were observed in the utility of the bars.
3. *Performance help predicts experience.* Our results show that the death rate and timeout rate are predictors for competence and tension.
4. *The experience enhancing bar resulted in a more consistent experience of tension regardless of game outcome.* With the typical health bar, players would experience higher levels of tension only when they performed poorly (i.e., had a higher death rate). However, with the experience enhancing bar players experienced tension independent of how they performed in the game.
5. *The experience enhancing bar seemed to lead to changes in behavior.* Players with the experience enhanced health bar used assertive play at different times in the game than with the typical health bar.

Explanation of Results

While our game was designed to require the use of the health bar, players did not notice any manipulations with the bar and did not feel it was a key to playing or being effective in the game. Even though the manipulation was not spotted, the effects on experience, performance, and behavior were measurable and showed differences as a result of our health bar manipulation.

Our results suggest that the manipulation of data displays of health affects competence and tension as primary measures of intrinsic motivation, but not enjoyment and effort. The strong relation to competence makes sense, because measures of health are a common indicator of play performance. For example, the fighting game Tekken (Namco, 1994), highlights a player's success as a "flawless victory" when a player does not lose any health or Street Fighter 2 (Capcom, 1991) gives score based on the amount of health remaining.

We can also show that health manipulation affects tension; a result that confirms what designers have intuitively applied before—decreasing health faster early on, but then keeping the player on low health for a while increases the tension experienced. Interestingly, our manipulation has no direct effect on enjoyment and effort, suggesting that health bar manipulations can be used effectively to alter the "feel" of a game without necessarily affecting players' enjoyment or their willingness to work harder to achieve a given goal.

While it might not be surprising that manipulating health will change play experience given our game design, it is surprising how effective it was given our rather simple and small manipulation.

After establishing that death rate and timeout rate strongly predict competence (R^2=.42), and to a lesser extent tension (R^2=.052), we investigated the effect of health bar manipulation on experience (i.e., tension, competence). Interestingly, health information only affects the experience of tension—it is stable with the enhanced health bar and shows a positive relation between death rate and tension in the typical health bar condition. These findings have implications for game design by showing that game designers can manipulate the display of health information to keep a game tense, independent of how a player performs. This result is particularly important because it suggests that through the simple manipulation of how data is displayed, the overall experience can be altered and used to balance experience between players. In fighting games, for example, balancing is often done by applying handicaps to players, i.e., the stronger player has less health than the weaker player. Our results suggest that to keep the game interesting for advanced players the actual amount of health does not need to be reduced, but that it could be enough to simply change how health is displayed in the bar.

We designed our game to influence behavior—players have to balance how close they get to flames. In general, players can get close to flames to try and extinguish them as quickly as possible and trade in health in the process, or they can try to be more careful, taking time to position themselves to best extinguish a fire while minimizing health loss. Our data suggests that players with the experience enhancing bar charged into the fire in the last seconds but stayed slightly more conservative over the course of a level—players in the typical health bar condition showed the opposite pattern. While the direct effect on behavior requires further investigation, our results suggest that health bar manipulation induces a more conservative play style. The passive play style led players to increased aggression in later stages of a level. From a game designer's perspective, being able to form assumptions about how players will behave depending on their health information is important. For example, consider the design of dynamically generated content. Generating encounters using a health bar that punishes engagement with intense health loss might result in a more intense experience and be ideal for later levels. However, the same approach might be a bad choice for early tutorial levels, because players would play too conservatively. Our behavioral findings suggest that designers need to carefully consider when and why players would show assertive behavior and how it relates to the intent of design.

In summary, our results show that health bar manipulation affects experience, performance, and behavior, and provides new game design insights and possibilities. Designers can leverage data display misrepresentation as an unobtrusive technique that has relevant effects on players through a subtle and simple manipulation.

Implications for Designers

Our game was specifically designed to study the effects of data display manipulation on play. As such, we crafted our game in a way that required players to make use of the information in the bar. However, our bar does align closely with bars in commercial games (Doom and Assassin's Creed). Like our game, these games require players to monitor health, avoid death, and make decisions about actions to take. These similarities suggest that experience enhancing bars like ours could be applicable to a wide variety of games.

Designing for Emotional Complexity. While high tension and lower competence might be thought of as negative or undesirable outcomes, designers might try to induce these experiences to engage players and create a feeling of depth of play, while still targeting an overall fun play experience (or not). Recently, researchers have highlighted how the focus on "positive" affect alone might miss out on the opportunities that the interplay between positive and negative emotions might offer [10, 25]. Our work recognizes this view and our findings can help designers achieve a desired play experience through data manipulation.

Competence is related to the experience of overcoming challenge and tied to our perception of difficulty; i.e., a player who struggles to overcome a challenge will likely perceive the challenge as being difficult in relation to their own ability. The balance between challenge and ability and their effect on experience is most famously captured in Csikszentmihalyi's notion of flow [15]. The concept of flow suggests that we experience deep engagement when challenge and ability align. In our work we show that we can artificially manipulate competence, which has implications for perceived game difficulty. Future work should assess how perceived difficulty—changed by data manipulations—can influence flow.

In many ways data display misrepresentation offers an attractive option to fine tune play experience. Considering that during the development cycle technical dependencies make it more and more difficult to introduce changes, tools such as these are important for game designers, because they allow the introduction of adjustments to overall play experience with few dependencies.

Fostering Player Experience through Health Bars

Most health bars in games are strongly connected to the concept of competence—they represent how well a player is doing in relation to their environment and indicate the player's ability to survive difficult encounters. The health bars in Redline also falls in the category, since it is one of the main ways players receive feedback it can be seen as an indicator of competence.

Health bars, however, can be used in ways other than for assessing competence. For example, to promote choice and different play styles, in Borderlands 2 (Gearbox Software, 2012) the actual health of a player is augmented through the players choice of a shield. The kind of shield players equip affects the play style of the player—some shields allow the player to play more assertively and to enter melee fights, while other shields give lots of bonus but don't protect the player well resulting in a more passive play style. Through choosing a shield, players can alter the experience they are having and express their personal preferences.

Another way health bars can be used is to enhance the experience of connectedness with other players. Many games like World of Warcraft (Blizzard 2004) or Team Fortress (Valve 2007) feature healing characters (e.g., priests, shamans, or medics) that can recharge the health of teammates. Players need to interact with each other to maximize their play experience resulting in stronger connections through health-related interactions between players.

As the above examples show, health plays a central role for creating valuable experiences in many games. Investigating how health is used to foster different experiences and how health bar manipulations can be used to alter these experiences are relevant questions for future research.

Considerations for Manipulating Data Displays

While our study did not solicit player opinion on the use of misrepresentation, our experience enhancing bar design was based on examples from well-known and popular commercial games (Assassin's Creed and Doom). The fact that misrepresentations are already in use, and that some are much more apparent than what we tested, suggests that players are at least generally aware of this, and open to it. Recent findings in hidden manipulations of input for the purpose of player balancing (e.g., [6, 13, 32]) support the idea of players being receptive to the idea of misrepresentations as long as it has a positive impact on experience. Our work, however, does allow us to comment on at least two situations where designers must be careful with the use of misrepresentation.

First, with the growing popularity of e-sports and competitive gaming, some players have on increased focus on optimizing behavior and performance. In these situations, the design of widgets and data displays are often done with a focus to maximizing usability and accuracy [36]. We see our own experience enhancing health bar design as being potentially problematic in such situations. Since the experience enhancing bar changes the effect size in the bar for different amounts of health, we suspect that this could lead to inaccuracy in reading data in situations where precise and time-sensitive decisions must be made.

Second, and related to the last point, is that manipulations may have a negative impact on learning and adoption of expert behavior. We believe this could be the case with our experience enhancing bar. The experience enhancing bar may have led players to behave less assertively early in levels, and more assertively later on. If so, this behavior is suboptimal for our game. This is because fires in the game grow over time, this suggests that players are better to be assertive earlier in a level and extinguish as many fires as possible to reduce the total amount of work required, rather than later in a level when fires have a chance to grow (causing more health loss and increased time to be extinguished). This observation is an important lesson, while our health bar did increase the tension experienced (as designed), it may have had a negative effect on learning.

Overall, these examples show that it is critical for designers to consider both performance and behavior—and not just experience— when designing misrepresentations in data displays or other aspects of game play.

Limitations

Although our findings have opened several new directions for future research, our work has several limitations that should be investigated to better understand the generalizability of our results. First, we have only compared two different health bars. It is not clear how different mappings using different representations (e.g., diegetic representations) or different health mechanics (e.g., discrete rather than continuous health) might affect our results. Further, we do not know whether our approach might work in different types of games (e.g., fighting games), different types of data displays (e.g., score display), or whether social/multiplayer settings might influence the effects we saw. Exploring other possible contexts around data misrepresentation will be an interesting direction for future work.

Finally, the effect sizes we found are rather small, which is common in games research and can be explained through the complex nature of games and individual differences in experience. Further, in our study, we used a rather simple manipulation. Hence, more prominent manipulations—for example, even larger health losses at the beginning—would likely produce larger effect sizes.

While we took care in choosing simple health bars that are representative, future research that replicates and extends our findings in various scenarios is needed to further inform the effective uptake of data misrepresentation.

5 CONCLUSION

In this paper, we have described a first study of data display misrepresentations in games. Our work has provided new findings that demonstrate that simple, subtle data misrepresentation can meaningfully alter play experience. What is extremely promising from our findings is that this type of display manipulation may allow designers to help provide a more stable play experience for players across a wide range of skill levels.

While we highlight that designers must remember that small manipulations can impact player behavior and performance, our findings suggest that they do not necessarily have an impact on enjoyment or willingness to work towards goals. For designers our work means that there is a tool that can be used to alter the feel of the game, and it can be readily applied even late in development because it does not impact many other aspects of play. While our findings immediately inform designers, we have also identified future research possibilities on the implication of subtle manipulation of data displays on player experience, performance, and behavior.

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