From Objective to Subjective Difficulty Evaluation in Video Games

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Abstract. This paper investigates the perception of difficulty in video games, defined as the players' estimation of their chances of failure. We discuss our approach with regard to the psychophysical studies of subjective difficulty and to the cognitive psychology research on overconfidence bias. We assume that the strong motivational pull of video games may lead players to be overconfident and underestimate their chances of failure. Our method is tested within three games related to three types of difficulty, where the players have to bet on their capacity to win each challenge. Results confirm the existence of a gap between the players actual and self-evaluated chances of failure. More precisely, players seem to strongly underestimate high levels of difficulty. Results do not show any influence of the players gender, feeling of self-efficacy, risk aversion and gaming habits on the difficulty estimation error.

Keywords: User Modelling · Affective HCI, Emotion, Motivational Aspects · Tools for Design, Modelling, Evaluation · Fun / Aesthetic Design

1 Introduction

Jesper Juul proposes to define a video game as "*a rule-based formal system with a variable and quantifiable outcome, where different outcomes are assigned different values, the player exerts effort in order to influence the outcome, the player feels attached to the outcome, and the consequences of the activity are optional and negotiable*" [1]. In this definition, the player *exerts effort* to influence the outcome, which emphasizes the fact that a game must have a certain level of difficulty to be considered as such.

Many authors acknowledge challenge as one of the most fundamental aspect of video games' inherent appeal. Malone proposes three features of computer games that make them so captivating: challenge, curiosity and fantasy [2]. In his model, challenge is directly related to the game's difficulty and corresponds to the uncertainty for the player to reach the game's goals. Lazzaro proposes a four factor model, where *Hard Fun* is related to the feeling of overcoming difficult tasks [3]. Sweetser et al see also challenge as one of the most important part of their Game Flow framework [4]. Their work stems from Mihaly Csikszentmihalyi's Theory of Flow [5], who has been trying to figure out the properties of activities showing a strong, intrinsic ability to motivate. Csikszentmihalyi research states that these activities provide *perceived challenges, or opportunities for action, that stretch (neither overmatching nor underutilizing) existing skills* [5]. The study of large population of players in two commercial games confirm that players prefer specific levels of difficulty[6] Ryan et al study as well intrinsic motivation and apply their Self-Determination Theory to video games. They show how enjoyment is related to the feeling of *competence*, which relies on an optimal level of challenge, and thus, to the game's difficulty [7]. Jesper Juul provided insight on how failure, and thus difficulty, is one of the core aspects of video game enjoyment and learning progression [8, 9].

In order to foster and maintain the players' motivation, it is thus fundamental to correctly set the difficulty of a video game. One can provide different difficulty settings for the player to select, or use an algorithm that adapts the gameplay's difficulty in real time to match the game designer's theoretical difficulty curve with regard to the current player skills [10–12].

It requires beforehand to evaluate the game's difficulty. The game designer might provide a heuristic which may or may not express the game's difficulty. We may use sensors to estimate workload or affective state, but currently only in a lab setting and this question is still by itself a research topic [13, 14]. We could also try to estimate the players' chances of failure [15]. All these approaches provide insight on a specific aspect of a game's difficulty.

The point is, difficulty is by itself a complex notion. We may draw distinctions between *skill-based* difficulty, *effort-based* difficulty [16], and between *sensory*, *logical* and *motor* difficulty [15, 17]. Moreover, video games are created for an aesthetic purpose, evoking specific emotion in the player [18]. Thus, we must draw a fundamental distinction between *objective difficulty* and *subjective difficulty*. Objective difficulty is to be directly estimated by observing gameplay variables and events, while subjective difficulty is a psychological construct of the player. When adapting a game's difficulty, especially when using a dynamic difficulty adjustment (DDA) algorithm, we rely on an objective estimation of difficulty, which may be quite different to what the player actually feels while playing the game.

The main objective of this paper is to study the relationship between subjective and objective difficulty, in the context of video games. We thus review different studies on both subjective and objective difficulty estimation in the next sections. First, we present the psychophysical approach of perceived difficulty. Second, we report cognitive psychology studies on overconfidence. Then, we introduce our method for measuring objective and subjective difficulty. Objective difficulty is modelized using a logit mixed effect regression to estimate the player's actual chances of failure for a given challenge. Subjective difficulty is considered to be the player's estimation of his chances of failure, that we gather using an in-game bet system. We then present the three games we developed for this study, allowing us to separate logical, motor and sensory gameplays. We detail and discuss our results in the last sections.

2 Psychophysical approach to subjective difficulty

Many studies have tried to clarify the link between subjective and objective difficulty in various tasks: Raven's progressive matrices, digits memorization, visual search of letters, wire labyrinth [19, 20], Fitts' tapping task [21, 22], dart throwing on a moving target [23], rock climbing [24] or reaction time, even while riding a bike [19, 25]. All these experiments take a psychophysical approach, trying to estimate the link between objective difficulty as a stimulus, and subjective difficulty as a perception or evaluation of this stimulus.

These studies use various techniques to estimate objective difficulty, and often tend to draw a distinction between objective difficulty and performance. For all the Fitts's tapping task, authors use the Fitts's law [26] as a measure of objective difficulty, and time as a measure of performance. When such a law is not available, they rely however solely on performance, e.g. response time or success frequency [23, 20], or select a variable highly correlated with perceived difficulty like electromyographic data from a specific muscle in the rock climbing experiment [24]. Also, in these studies, objective difficulty is never assessed with regard to each subject abilities, but across all or a few subgroups of subjects. In our research, we do not rely on any specific objective difficulty estimation but follow a more generic approach that allows cross-game comparisons. We estimate a mapping between the challenge's variables and the player's probability to lose this challenge. We also use a mixed effect model that can take into account each player's abilities.

In these studies, subjective difficulty is assessed by the subject using a free scale. Very often, a reference value is given to the subject, e.g. subjective difficulty of 10 for a specific task [21]. Deligniere has proposed the DPE-15 scale, a 7 points Likert scale with intermediate values, for a more convenient and comparable measure [23]. In our experiment, we integrate the measure to the gameplay and will use a specific 7 points scale, described in section 4. To avoid personal interpretation of the notion of difficulty evoked in the previous section, we will concentrate on the success probability, as estimated by the player.

Except in Slifkin & Grilli [21], all subjective evaluations are done at the end of the challenge, often after having repeated the challenge many times. We think that to understand what the player feels while playing a video game, and not when thinking back about a past game session, it might be interesting to have a look at the player's evaluation of the current difficulty, during each one of his attempt to overcome a challenge. As our measure of subjective difficulty is an estimation of failure chances, it can be integrated to the gameplay and thus be repeated more often without pulling the player out of the game (see section 4).

3 Overconfidence and the Hard/Easy effect

We define subjective difficulty as the players' own evaluation of their chances of failure. This evaluation is a complex cognitive process, often rushed, based on the interpretation of incomplete information about the game state, on in-game performance feedback, and on assessments of the players own knowledge and skills with respect to a specific challenge. Cognitive psychology research on judgmental heuristics studies how such a reasoning can be biased, and can help us understanding how players may have a wrong evaluation of their chances of success.

Heuristic approach to judgment and decision-making has opened a vast field of research to explain human behavior in a context of uncertainty. Kahneman & Frederick [27, 28] consider that, confronted to a complex decision, people substitute one attribute of the decision to a simpler one, more available, to reduce cognitive effort. In some cases, the use of judgmental heuristics can lead to fundamental errors, called *cognitive biases* by Kahneman & Tversky [29].

The overconfidence effect is one of those. Well-studied in the financial field, this behavior relies on a surrealistic evaluation of our own knowledge and skills, leading to an overestimation of our abilities or of those of others [30–34]. Overconfidence seems particularly interesting to study with regard to video games as those are essentially built to motivate their players. Self-efficacy theory of motivation states that having a strong confidence in his future chances of success is a key aspect of motivation [35]. Video games, using for instance a well crafted difficulty curve, may manipulate the players' perception of their success chances to keep them motivated.

Overconfidence has already been studied in many games. During games of bridge, beginners or amateurs players can misjudge both their performances and play outcomes [36]. The same results were noticed about poker's players, where beginners show inferior capacity to predict their odds of winning [37], during game tournament of poker and chess game [38], or associated with gambling games [39, 40]. In brief, the overconfidence effect appears when the players have a limited knowledge of the game and for any type of game, whether it is a pure game of chance, like fruit machine, or a skill based game, like chess game.

There exist many situations and cognitive biases that influence the overestimation or underestimation of one chances of success, like the level of expertise [41, 42], the *gambler's fallacy* [43, 44], the *hot hand bias* [45, 44], the *illusion of control* [46, 47] or the *hard/easy effect*. All these aspects of overconfidence are worth studying in the context of video games but for this research, we chose to focus on the *hard/easy effect*. The *hard/easy effect* specifies that for low and high level of difficulty, decision-makers cannot estimate the real difficulty of the task [48]. For low levels, they will underestimate their chances of success, whereas for high levels, they will overestimate them [41, 33].

Starting from the hard / easy effect, our research focuses on two main points. First, from a methodological point of view, we want our experiment to be as close as possible to a real video game. Thus, we use a dynamically adjusted difficulty that starts from a low level of difficulty, which is a key element of game design. We also do not evaluate players' confidence by directly asking them if they feel confident on a percentage scale, but instead we use a betting mechanism integrated to the gameplay, avoiding to break the player's immersion. Second, our research distinguishes between three types of difficulty. We use three different games, each one of them focusing on a specific kind of difficulty. We fully describe our experiment in the next section.

4 Experimentation

As stressed out in the previous sections, there exist different types of difficulties in video games. In this experiment, we want to assess them separately, in an attempt to distinguish between various facets of video games. We follow Levieux et al [17, 15] approach and consider three categories of difficulty in games: sensory, logical and motor. Sensory difficulty relates to the effort needed to acquire information about the game state. Logical difficulty corresponds to the effort needed to induce or deduce, from the available information, the solution of a problem in terms of action(s) to perform. Lastly, motor difficulty is related to the physical agility needed to perform these actions. To realize an accurate analysis of the player's behavior for each of these types, the experiment is split between three specifically designed games.

In this experiment, we choose a general, practical approach and estimate the probability that a player has to fail at a specific challenge, with respect to his current skills [15]. As the player will be asked to evaluate his chances of success, there is no risk for the player to hesitate between effort-based and skill-based difficulty. Moreover, our definition of difficulty directly follows Malone's definition of challenge, as a source of uncertainty in video games [2]. Indeed, uncertainty about success or failure is what Costikyan calls *uncertainty of outcomes* [49]. Also, to distinguish between logical, motor and sensory, we designed three different games which are described in section 4.3. In order to maximize the player motivation and propose an experience as close as possible to an actual game, the system adapts dynamically the difficulty, analyzing the player's successes or failures. Many games use a dynamic difficulty adaptation, like racing games (mostly rubber banding like in *Mario Kart* series), RPG (e.g. *Fallout* series) or FPS (e.g. *Unreal Tournament* series) where the difficulty to defeat an opponent depends on the players level. Games without dynamic difficulty adaptation can use a predetermined difficulty curve, based on the mean level of the players. On the opposite, few games use a totally random difficulty, and for those (e.g. *FTL*, *The Binding of Isaac*), there is still a global progression. Thus, randomness would be more convenient for statistical analysis, but also highly questionable from a game design perspective.

Furthermore, to avoid any memory bias on the past challenge and to better monitor the actual feeling of the player, we measure the subjective difficulty during the game session and not with post-experiment questionnaires [50]. To be able to do so without pulling the player out of the game, we propose to use a bet system, described in the next section.

4.1 Measuring Subjective difficulty

Our proposition adopts the cognitive psychology tools to measure overconfidence, and integrates them to the gameplay. Our goal is to avoid any disturbance during the game session, to keep a high level of engagement and motivation. The measure is made before the players choices, as a pre-evaluation, but after giving them all the elements useful to perform their judgment. We use a bet system based on a 7 points Likert scale, which is integrated into the game progression and, thus, is related to the players' score. If the player wins, the amount of the bet is added to his score; and if he loses, this amount is subtracted, improving players concentration on their own evaluation. An in-game question is used as instruction for betting and as a reminder for the players to strictly assess their own confidence.

Measurement of the subjective difficulty is based on the players' bet, noted D_{subj}. With b being the bet value we use the formula $D_{subj} = 1 - \frac{b-1}{6}$ to get the estimated chances of failure.

4.2 Measuring Objective difficulty

The objective difficulty of a challenge is estimated from the players' failures and successes for that challenge, as Levieux et al defined it [17, 15]. In order to take into account personal differences, we estimate for each challenge the objective difficulty by fitting a logit mixed-effects model [51]. Time and difficulty parameter of each challenge (e.g. cursor speed, number of cells...) are used as fixed effect parameters, and we add random intercepts. We use a mixed model through repeated evaluations of the same subject. The random intercepts give us a coefficient for each players that we use as a global evaluation of each player's level. The gap between the players' objective difficulty and their evaluation of odds of winning is called the *difficulty estimation error*. The design of the three games, each one based on a difficulty type - logical, motor or sensory -, is detailed in the next section.

4.3 Game's description

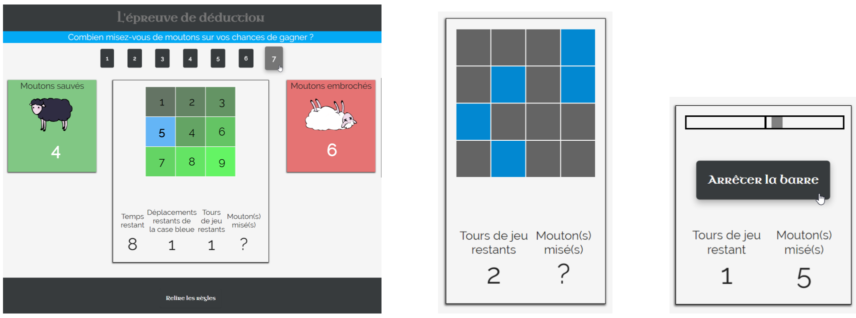
The experiment is based on the observation of the players' bet for the three dimensions of difficulty. Each dimension is represented by a specific game, described as follows, for which all the adjustment variables for the challenges are pre-established and common for all players. A first series of playtests was also conducted with the target audience, in the same settings used during the experiments, for gameplay calibration.

A brief story was included in order to improve the player's motivation and to have a narrative justification of the bet system. In the game universe, the players have to save citizens of a mysterious kingdom, transformed into sheep by the local sorcerer. The players challenge the sorcerer during three tests, one for each kind of difficulty. The players' unique objective is to save as many sheep as possible. Then, each game is an opportunity for the player to save doom citizens, by betting one to seven sheep on their odds of winning.

All games show a common user interface, except for the central frame that depends on each sub-game (figure 1). All important information is displayed at the bottom of the central frame, like the number of remaining turns, the global score, and remaining number of actions for the logical game. Directives are placed just below the main title, on a colored banner, blue for directives, red for corrective feedbacks. A rules reminder is accessible at the bottom of the screen.

Feedbacks are provided all along the player's progression, right after the results presentation. Positive (on green background) and negative ones (on red) are displayed on the two sides of the screen, allowing the players to constantly follow their amount of saved and lost sheep. Sounds are associated to them; one bleating for a saved sheep, one sorcerer's mocking laugh for a lost one. Animations are used to aim for a more stimulating in-game interface.

For each game, we modify the difficulty using a *difficulty parameter*. This parameter varies from 0 to 1 and is used to interpolate gameplay parameters, defined in the next section. For all games, the difficulty parameter starts at 0.2, and increases or decreases by 0.1 step after each turn based on players' success or failure.



(a) Logical task (b) Sensory task (c) Motor task

Fig. 1: Game interface for the logical, sensory and motor tasks. Logical task is shown with the whole user interface, while we only show the center frame for the motor and sensory task. Screenshots were taken for the easiest levels of difficulty.

Logical difficulty The logical task is based on a well-known sliding-puzzle game. The players have to restore the numerical order of a 300 pixels wide grid composed of 9 squares. The fifth square, originally placed on the middle of the grid, is the only one that can be moved. This square can only be moved by switching position with another, adjacent square (figure 1a). At the beginning of each turn, before displaying the grid, the fifth square is randomly moved several times, and the mixed up grid is displayed for 20 seconds before disappearing. The players have all the information required to place a bet: the remaining time is visible and the number of inversion is specified. After betting, the grid will reappear and the players can begin to move the fifth square to restore the numerical ordering. The difficulty parameter allows us to adapt the difficulty by changing the number of steps during the randomization of the grid, linearly from 1 to 11 steps.

Sensory difficulty For the sensory difficulty, we designed a 300 pixels wide grid composed of multiple squares (figure 1b). At the end of a countdown timer, five of them will fade out during a limited time, that we can approximate as follows, with t being the fade out time and d as the difficulty parameter: $t = d^2 - 0.24d + 1.2$[1]. Then, the players have to find them back, by clicking on the grid. The selected squares are displayed in a blue color, whereas the other remains in a gray one, to avoid any color perception bias. The winning squares will be shown after making a bet, over the players' selection. By doing so, we want to induce a near-miss effect, allowing the players to see if they selected all, some or none of the winning squares. The countdown timer is blocked on 3 seconds. The number of squares will vary with the difficulty of the task: when the player wins, the grid will gain one square on each side. But the surface of the grid constantly remains the same, implying that the squares will become smaller after a winning round. The maximum difficulty levels is a grid composed of 11 squares on a side; the minimum levels is one composed of 4 squares. This values are linearly interpolated for in-between difficulties using the difficulty parameter. Winning squares' random location is chosen to avoid the most simple patterns, and thus, to minimize pattern-induced variations of difficulty for a specific difficulty parameter value. For example, for a 5 squares sided grid, any adjacent winning squares are forbidden.

Motor difficulty The motor difficulty is a basic and common reflex-based task. A cursor goes back and forth along a horizontal segment, with a linear speed. The players have to stop the cursor when it covers a black mark at the center (figure 1c). They can only stop the cursor by clicking on a button. Before that, the players have to bet on their chances to success. This evaluation is not timed. The difficulty of the game is based on the cursor's speed, ranging linearly from 100 to 400 pixels per seconds. The sliding area is 320 pixels wide, the cursor is 15 pixels wide, and the black target 2 pixels wide.

Protocol consistency These three tasks, although different in nature, do share a similar protocol and always provide the player with the elements needed to evaluate the difficulty. For the motor task, players can observe the moving cursor before betting. For the logical task, the game displays the number of inversions and let the player look at the problem for a fixed duration. For the sensory one, where the visual memory is crucial, the player select tiles to solve the problem, but without any feedback, before betting. Previous playtests showed that the task was really frustrating if the player had to stop focusing on the grid for betting without selecting the tiles. Each game has a specific gameplay, as each one focuses on a specific dimension of difficulty. Results can thus be compared between games, while carefully discussing the gameplay differences.

[1] This equation is a quadratic regression of the fade out time. In the game, the color is incrementally modified in the game loop, but plotting this equation is much clearer than reading the color update code.

4.4 Procedures

Experiments were conducted in Paris at the *Cité des sciences de l'industrie*, a national museum dedicated to science and critical thinking, during ten days of the All Saint's vacations. The target audience was composed of young gamers and non-gamers population, and they were free to participate. A few declined the invitation, judging their experience about video game as too weak, or by lack of interest about participating in a science experiment.

Nine laptops, with the same configuration, were dispatched in an isolated room. Each one had a mouse and a headset. The main program runs on a web browser, and was developed with JS, HTML5 and CSS. Participants were informed that the game's goal was to save as much sheep as possible, and of the duration of the experiment, approximately 40 minutes, questionnaire included. They were not allowed to communicate between them during the session. Before starting to play, the participants had to fill an online questionnaire employed to realize several user profile:

– **A gaming habits profile**, based on the amount of time that participants spent playing board games, video games (including social games) and gambling games.
– **A self-efficacy profile**, based on General Self-Efficacy scales [52, 53] and adapted to video games situations. This part of the questionnaire is only accessible for the participants who answered yes to the question *"Do you consider yourself as a video games player?"* in the gaming habits section. The purpose of it is to verify any negative or positive effect of the participant's gaming capacities self estimation on his confidence.
– **A risk aversion profile**, based on Holt and Laury Ten-Paired Lottery-Choices [54] in order to evaluate the impact of risk incentive on the players' confidence.

The game macro-progression is the same for all players:

– A **prologue** introduces the story before a random selection of the three tasks.
– A specific page presents **the rules** of the mini-game, just before playing it. Players can take as much time as they want to understand them.
– Each task, or **mini-game**, lasts 33 turns. The first three turns are used as a practice phase. At the end of this practice phase, the score is reset to zero.
– The **turn progression** is identical for all the mini-games. First, players have to observe the current game state in order to evaluate the difficulty. Then, they have to bet from 1 to 7 sheep about their confidence to succeed. The same question is always asked to the player: "How much sheep are you betting on your chances of winning?". This question allows us to estimate the players' perception of his chances of failure. By validating the bet, the system unlocks the game and players can try to beat the challenge. The result is presented on screen and the score is updated at the same time. Then, a new turn begins, with the adequate modification of the difficulty level: when players win, the difficulty increases; when they lose, the difficulty decreases.

- After each task, a screen allows the player to check his/her progression and score, and works as **a game hub**, enabling the connection to an other task.
- Then, by completing the three tasks, a brief **epilogue** of the story announces the player final score, the sum of all sheep won and lost.

To avoid any order effect, the selection of the task is randomized. The best score of the day was written on a board, visible by the players. At the end of each turn, the designed difficulty of a challenge, the players' bet, their score, are recorded on CSV files.

5 Results

A total of 80 participants have played the games. Some of them have left the experiment before the end, but we keep results for all completed games, giving us a total of 6990 observations. For each task, we remove outliers, such as players who did not use the bet to perform a self-assessment, placing always the same bet, or players with outlying performance. A very low score may reflect some user experience issues, and some players took advantage of the adaptive difficulty system in order to maximize their score, by deliberately losing with a low bet, then by placing a high bet on the next easier challenge and so on. Nine outliers have been removed: one from the motor task, three from the perceptive task, and six for logical one. We thus removed 300 observations from the dataset.

5.1 Modeling objective difficulty

As explained in section 4.2, we perform a logit mixed effect regression to evaluate the objective difficulty. For each task, we report the conditional R^2, i.e. using both fixed and random effects [55] and evaluate the model by performing a 10-fold cross-validation, using our model as a binary predictor of the challenge outcome (figure 2).

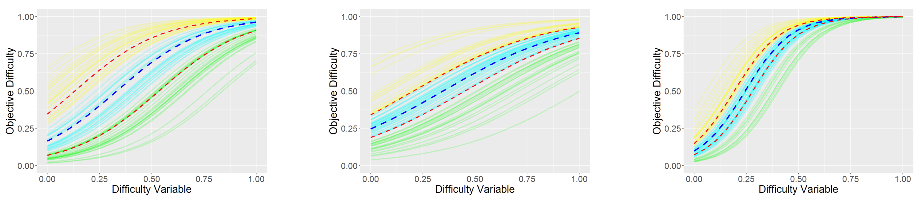
Parameters / Tasks	**Logical**	**Motor**	**Sensory**
Difficulty parameter	4.88 ($p < 2e-16$)***	3.23 ($p < 2e-16$)***	9.1 ($p < 2e-16$)***
Time	-1 ($p = 2e-6$)***	-0.46 ($p = 0.0051$)**	-0.37 ($p = 0.0454$)*
σ(random intercepts)	1.24	0.83	0.76
R^2	0.48	0.28	0.42
Cross Validation	0.66	0.61	0.69

Fig. 2: Modeling objective difficulty for each task: logit mixed effect regression results for difficulty and time over failures.

As can be seen in figure 2, the difficulty parameter is always highly significant, and has the strongest effect on failure probability, especially for the sensory task, which means that we were indeed manipulating the objective difficulty by changing this parameter.

The effect of time is always negative and significant. This means that, if the difficulty parameter stays constant, objective difficulty seems to decrease with time. This might indicate that players are actually learning as their success rate improves with time for a given difficulty parameter value. Time effect is the strongest for the logical task (-1) which is coherent with the fact that the player should learn more from a logical problem than from a purely sensory motor one (respectively, -0.46 and -0.37). Also, it may be noted that we have the highest standard deviation of random intercept for the logical task, which means that inter-individual differences are the highest for this task.

The link between the difficulty parameter and the objective difficulty of the game can be plot to better understand each challenge difficulty dynamics. We choose to plot objective difficulty over difficulty parameter at time $t = 0$. We also used the random intercept to separate the player in three groups of levels using k-means (fig. 3).



(a) Logical task (b) Motor task (c) Sensory task

Fig. 3: Objective difficulty for each task at $t = 0$. Blue dashed line is the median player, red dashed lines show first and last quartiles. The less efficient players are in yellow, medium players in cyan and best players in green.

Curves in figure 3 give us information about our design of each task's difficulty. We can see that the logical task is the most balanced, with objective difficulty being the closest to the difficulty parameter value. The motor task is is a bit too hard for low difficulty levels: objective difficulty is around 0.25, when the difficulty parameter is 0. Also, sensory task should vary more slowly : objective difficulty is maxed when the difficulty parameter is only 0.5.

Figure 4 shows the progression of objective difficulty during the game. The curves confirm the balancing of each task and the efficiency of the difficulty adaptation system, as the players reach the average objective difficulty level (0.5) in all cases. The logical task starts at 0.2 for medium players and goes up. The motor task is too hard at the beginning, and thus bad players see a decrease of difficulty with time. Sensory task shows a "wavy" pattern which might be related to the fact that the difficulty is less stable for this game. Indeed, the difficulty

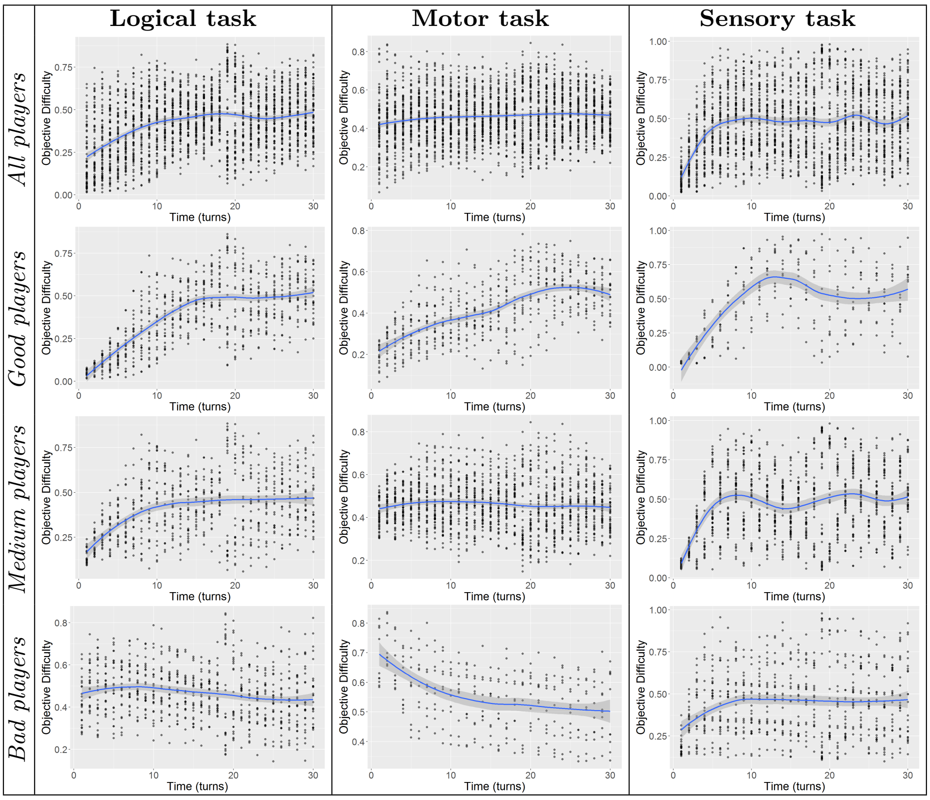


Fig. 4: Progression of objective difficulty with time for all tasks and players during the whole play session. Blue line is the median players, dots represent the observations for each turn.

parameter varies by 0.1 step for all tasks, but as the maximum objective difficulty is already reached at 0.5, it varies approximately twice faster than for the logical one.

Overall, the objective difficulty model is the weakest for the motor task with a low conditional R^2 (0.28) and the lowest prediction accuracy (0.61). R^2 and prediction accuracy are higher for the logical ($R^2 = 0.48$, $accuracy = 0.66$) and sensory task ($R^2 = 0.42$, $accuracy = 0.69$).

5.2 Differences between objective and subjective difficulty

To investigate the differences between objective and subjective difficulty, we separate the data into 16 equally sized bins using the objective difficulty estimated by the mixed effect model. In each bin, we compute, for each player, the mean subjective difficulty. We thus have only one value by player in the bin, and each observation is thus independent from the others. Then, for each bin, we test the null hypothesis that the bin's median subjective difficulty's is equal to the objective difficulty at the center of the bin's interval. We use a Wilcoxon Signed Rank Test and compute the 95% confidence interval (red bars) and pseudo median (black dot and triangles), plotted in figure 5. We only show the pseudo median and confidence intervals for bins with enough samples to run the Wilcoxon signed rank test, and blue line represents our null hypothesis, where objective difficulty equals subjective difficulty. Results allow us to safely reject the null hypothesis for each median represented by an empty triangle in the plots, where Wilcoxon signed rank test p-value is lower than 0.05.

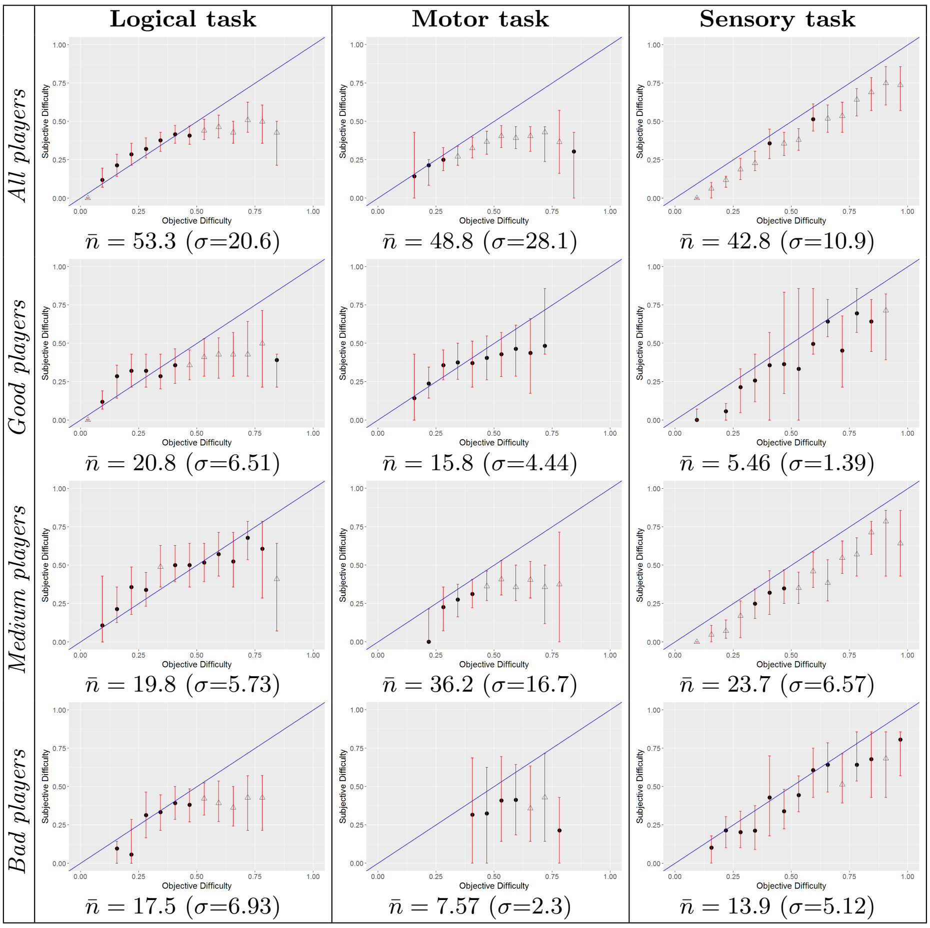


Fig. 5: Subjective and objective difficulty for all tasks and players. $\bar{n}$ is the mean (sd) number of players in each bin for each task and level.

There seems to be a strong *hard effect* for both logical and motor tasks. For the sensory task, players seem to be slightly overconfident for all objective difficulties. When split by levels, the effect seems stable for the motor task, but the relatively low number of bad ($\bar{n} = 7.57$) and good players ($\bar{n} = 15.8$) might lead to the non significance of the results. The same can be seen in the sensory task where pseudo medians are always under the calibrated evaluation, but results lose significance with the decrease of subjects number. However, for the logical task, bins size are equivalent for the three conditions, but medium players seem better calibrated. This result should be investigated further in a specific experiment to provide more insightful results.

5.3 Influence of participants' profiles on the subjective difficulty

We conduct several tests in order to analyze whether gender, gaming habits, assessment of self efficacy and risk aversion have an impact on players' levels and difficulty estimation error. We take the random intercept of the objective difficulty model as each player's level.

Out of 80 participants 57 are males and 23 are females. 49 of them daily play video games, and 12 weekly. 31 play board games monthly, and 36 almost never. 58 are risk-averse, and for the 46 of the participants who answered the self-efficacy questionnaire, 28 tend to see themselves as efficient players and all esteem themselves as superior to a medium player.

First we tested gender influence on players' levels and difficulty estimation error with a Wilcoxon rank sum test. The null hypothesis is that both of them are pulled from the same distribution for each gender. The test was only significant for players' level. Females players seem to be performing less on the motor game ($W = 255$, $p = 2.6^{e-5}$), with a difference in location of -0.67, and on the logical game ($W = 341$, $p < 0.01$), with a difference in location of -0.82.

We tested how gaming habits, self efficacy and risk aversion impact on level and difficulty estimation error using the Kendall's rank based correlation test. The test was only significant for the influence of risk aversion on players' level, for the sensory game ($z = 3.3093$, $p < 0.001$) with $\tau = 0.29$ and for the logical game ($z = 3.2974$, $p < 0.001$) with $\tau = 0.28$, meaning that for both these games, risk averse players tend to perform better. Thus, in our experiment, we did not detect any impact of gender, playing habits, assessment of self efficacy and risk aversion on difficulty estimation error, only on player's actual performance.

6 Discussion

6.1 Influence of difficulty and hard effect

We observe that the players estimation of difficulty is always below the actual objective difficulty, except for the logical and motor tasks on the easiest difficulty levels. More precisely, motor and logical tasks show the existence of a strong *hard effect*, namely, an overestimation of the players' chances to success for the hardest levels of difficulty (figure 5). Contrarily to the cognitive psychology studies related to overconfidence, in addition to the *hard effect*, nothing seems to indicate any *easy effect*, namely an underestimation of the chances of success for the easiest tasks [48, 56].

The presence of a *hard effect* and absence of *easy effect* might be explained by the players' confidence towards the game designers: games are rarely impossible to finish. What makes games different from many other tasks is that difficulty is artificial created for entertainment, players know that given enough time, they are almost always supposed to eventually win. This may drive us to be over confident in their chances of success

Moreover, players' overconfidence and hard effect may be stronger in our games than in previous cognitive psychology studies because of player progression. Indeed, our games allow players to experiment, to learn from their failures and, thus, to increase their performance. This feeling of progression and mastery may help players to become more confident on their chances of success. In cognitive psychology studies, where general culture questionnaires are very often used, this might not be the case.

The player's global confidence towards the game and their feeling of progression and mastery are also enhanced by the use of DDA algorithm. By presenting the players challenges that are adapted to their current level, the game is neither too boring nor too frustrating, allowing them to stay motivated and to believe in the fairness of the game.

Also, during our experiment, it is to note that objective difficulty starts below 0.5, and thus that players face more easy challenges at the beginning of the game, when they do not know the game, than at the end. Previous studies on the *hard/easy effect* relies on general culture questions and thus players may be able to assess their knowledge and their chances to win from the very first question. Thus, we may postulate that players assessment of easy challenges is biased by their ignorance relative to the games' procedures. However, the motor task has an almost flat progression curve, and this task has no sign of an easy effect. Also, for sensory and logical task, both have more easy challenges at the beginning of the session, but for the logical task, we seem to be close to a small easy effect, and for the sensory, it's the opposite and player's are overconfident for easy challenges. There thus do not seem to have a clear impact of oversampling easy challenges at the beginning of the session on easy effect.

We may explain the results' differences between sensory against both the logical and motor tasks by the nature of the subjective difficulty the players have to assess. As defined in our method in section 4.3, the bet system focuses on the players' estimation of their performance, and this estimation is not always performed in the exact same conditions. For the sensory game, the players can select the squares before betting, making the play effort before interpreting their chances of failure. Of course, they do not know about their actual performances, but they go one step further toward the completion of the challenge than for the two other games. Thus, they assess their chances of failure after having realized the exercise, and thus may have a more accurate feeling of the quality of their answer. For the two other games, they perform no manipulation and have to guess all the next steps. This design choice for the sensory task was made because we did not want to focus on memorization, but on the sensory aspect of detecting blinking squares.

It is to note that our result are different from those of psychophysical studies on subjective difficulty, where perceived difficulty seems to never reach a plateau and have a more linear or exponential aspect. We think that this is mainly the case because we ask player to predict the difficulty of a challenge, not to evaluate it after many repetitions. We think that our approach, closer tho the cognitive psychology approaches, may be closer to what a player really feels while playing.

Motor game is the task where the quality of our model is the lowest ($R^2 = 0.28$). It is by far the fastest game to play, where participants can complete quickly one turn after the other which may explain the higher objective difficulty variability. However, such design is representative of action games. Slowing the game's pace may produce more stable results, but the experiment will be less representative.

6.2 The player's profile impact

We do not find any evidence of the influence of the players' profile on their estimation of difficulty. It seems to be contradictory to the studies about overconfidence. Some aspects of the experiment may explain such results.

In a financial analysis field study, Barber & Odean [57] study overconfidence in order to explain the difference of trading's performance gender, concluding that men have a tendency to be more overconfident and less risk averse than women. We do not observe such behaviors, and we explain it mainly because our experimentation's protocol differ from Barber & Odean's study. First, the median age of our participants is 15 while their is 50. Then, their participants have a certain degree of expertise about investment, whereas ours do not know the content of the games before playing them. Moreover, we may postulate that our tasks are very abstract and less prone to culturally induced gender differences.

Risk-aversion is also a determinant of an excessive confidence [57, 34]. However we do not find any influence of the risk on the difficulty estimation error. Contrary to these studies, our participants' age is quite young. Also, the questionnaire relies on mental calculus and probabilities and might be less efficient on adolescents.

Stone [58] shows that initial and positive self-efficacy assessment may reinforce the participants' confidence and modify their performance, which is not the case in our study. However, in Stone's experiment, self-efficacy is assessed with regard to the given task, i.e. participants are asked to estimate their performance. In our study, we estimated self-efficacy using a general self efficacy questionnaire [52, 53]. However, if we use players' mean bet as a measure of self-efficacy, there is a clear relationship between self-efficacy, i.e. how high the mean bet is, and overconfidence, i.e. how high mean bet minus mean actual result is. This is not surprising, as objective difficulty is adapted to 0.5 for each player. Also, we do not find a link between mean bet and player performance.

6.3 Experiment's limitations

There are some limitations relative to our approach, and in particular to the bet system.

The bet system Our approach is based on the use of a bet system to measure the players' difficulty estimation error. First, this approach is limited to specific tasks, where the interaction rhythm can be combined with a recurrent question addressed to the player. Also, it is important to note that the bet is not strictly related to the confidence, as measured in cognitive psychology studies. For our games, the optimal strategy is to bet 7 when $D_{\text{objective}} > 0.5$, and 1 when $D_{\text{objective}} < 0.5$. Thus, our evaluation might be less accurate than confidence scales. Moreover, as we said in section 6.1, the bet system does not allow us to clearly distinguish between effort-based and skill-based subjective difficulties. New experiments can improve the separation between them.

Dynamic Difficulty Adjustment DDA is representative of how video games are designed, and must have a notable impact on the hard / easy effect. Such an adjusted curve should allow players to be more confident in their chances of success, and we should thus observe a weaker easy effect and a stronger hard effect than in a pure random experiment. Our experiment shows than when using DDA, players do develop a strong feeling of confidence in two of the three tasks. Nevertheless, be able to point out DDA as responsible of this overconfidence, we need and A/B experiment to compare our results to others based on a random difficulty system.

Motivational influences The actual performance of a player is both dependent on the task difficulty and on the players' effort. If the player is not motivated enough, he may correctly assess the difficulty but be less efficient because he does not want to make the effort. Video games' players experience various states of emotion [59, 8], including sometimes boredom or anxiety. As such, these emotions have to be taken into account in future experiment. We also have to note that only sensory and motor tasks induce a *near-miss effect*, while the players do not know if they were almost successful during the logical task. The *near-miss effect* may convict the players that they were almost winning, leading them to overestimate their chances of success for the next turn [39, 40].

7 Conclusion and Perspectives

In this paper, we investigate the players' perception of difficulty. We extend previous psychophysical and cognitive psychology studies by proposing a method to evaluate objective difficulty and focusing on video games.

First, results demonstrate the efficiency of our objective difficulty estimation. The mixed effect model allows us to easily take into account the difference between players. Results show a predictive accuracy ranging from 61% for the motor task, to almost 70% for the other tasks. Estimated objective difficulty is coherent with DDA, showing a convergence of objective difficulty to 0.5, for all groups and levels. We are also able to measure a learning effect, as a negative effect of time on objective difficulty for a give difficulty parameter value. This learning effect is coherent with the nature of the tasks, with a higher learning effect for the logical task.

Then, results confirm the existence of an unrealistic evaluation of the players' actual chances of failure. More specifically, players are always overconfident, except for low level of difficulty in the motor and logical task. Results show a strong *hard effect* for the motor and logical tasks, and no significant *easy effect* for all tasks.

We postulate that players' strong overconfidence might be explained by the fact that our tasks are video games. First, players know that games are made to be eventually beaten. Second, games allow players to get better and develop a sense of progression and mastery. Even more, the use of DDA should reinforce both of these experiment's aspects.

The absence of a hard effect on the sensory task may be clarified by the design of the sensory task itself, as the difficulty evaluation performed after players actually tried to solve the problem, and thus, they may have a better feeling of their performance.

New experiments will be conducted in order to improve our understanding of difficulty perception in video games. We want to explore the use of a random difficulty curve, to validate the impact of DDA on the hard / easy effect by comparing both experiments. Moreover, we plan to investigate the influence of the previous turns on the players' perception of difficulty. DDA creates a temporal relationship between the difficulty of subsequent turns and thus prevented us to realize the analysis on this experiment.

Then, we plan to verify the impact of feedbacks on the players' assessment of difficulty. Constant feedbacks about the decision process leads the participants to re-evaluate their judgments during the task, reaching a more accurate level [60]. Continuous feedbacks about the user's progression is a main feature of human computer interaction and, in particular, video games. It implies to distinguish between positive and negative feedbacks, or to test the influence of feedbacks' accuracy. Video games adopts various types of feedback in order to affect the players, to generate more uncertainty of the outcome and to improve enjoyment [59, 49].

It is to note than from a game design perspective, the presence of a hard effect has pro and cons. Hard effect is a good consequence of the game's motivational mechanics : if the player believes in his chances of success, then he may be motivated to play. However, having players believe that a challenge is easier than it is, especially in high level of difficulty, may also lead players to frustration because they will lose at challenges they thought they could win. The motivational aspects of the discrepancies between subjective and objective difficulty seems thus worthy of further investigation.

Finally, we plan to expand our approach with other measures of mental effort like eye-tracking methods that have been used to assess cognitive load related to computer interface [61], specially about memory and logical related tasks [62].

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References

1. Juul, J.: The game, the player, the world: Looking for a heart of gameness. In Raessens, J., ed.: Level Up: Digital Games Research Conference Proceedings. Volume 1. (2003) 30–45
2. Malone, T.W.: Heuristics for designing enjoyable user interfaces: Lessons from computer games. Proceedings of the 1982 conference on Human factors in computing systems (1982) 63–68
3. Lazzaro, N.: Why we play games: Four keys to more emotion without story. In: Game Developers Conference. (March 2004)
4. Sweetser, P., Wyeth, P.: Gameflow: a model for evaluating player enjoyment in games. Computers in Entertainment (CIE) **3**(3) (2005) 3–3
5. Nakamura, J., Csikszentmihalyi, M.: The concept of flow. In: Flow and the foundations of positive psychology. Springer (2014) 239–263
6. Allart, T., Levieux, G., Pierfitte, M., Guilloux, A., Natkin, S.: Difficulty influence on motivation over time in video games using survival analysis. In: Foundation of Digital Games. (2017)
7. Ryan, R.M., Rigby, C.S., Przybylski, A.: The motivational pull of video games: A self-determination theory approach. Motivation and emotion **30**(4) (2006) 344–360
8. Juul, J.: A Casual Revolution: Reinventing Video Games and Their Players. Mit press edn., Cambridge, USA (2009)
9. Juul, J.: The Art of Failure. 1 edn. The MIT Press, Cambridge, USA (2013)
10. Hunicke, R.: The case for dynamic difficulty adjustment in games. In: Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology, ACM (2005) 429–433
11. Andrade, G., Ramalho, G., Santana, H., Corruble, V.: Extending reinforcement learning to provide dynamic game balancing. In: Proceedings of the Workshop on Reasoning, Representation, and Learning in Computer Games, 19th International Joint Conference on Artificial Intelligence (IJCAI). (2005) 7–12
12. Vicencio-Moreira, R., Mandryk, R.L., Gutwin, C.: Now you can compete with anyone: Balancing players of different skill levels in a first-person shooter game. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, ACM (2015) 2255–2264
13. Rani, P., Sarkar, N., Liu, C.: Maintaining optimal challenge in computer games through real-time physiological feedback. In: Proceedings of the 11th international conference on human computer interaction. Volume 58. (2005)
14. Afergan, D., Peck, E.M., Solovey, E.T., Jenkins, A., Hincks, S.W., Brown, E.T., Chang, R., Jacob, R.J.K.: Dynamic Difficulty Using Brain Metrics of Workload. In Jones, M., Palanque, P., eds.: CHI '14 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Toronto, Ontario, Canada, ACM New York, NY, USA (2014) 3797–3806
15. Aponte, M.V., Levieux, G., Natkin, S.: Difficulty in Videogames: An Experimental Validation of a Formal Definition. In Romão, T., ed.: Proceedings of the 8th International Conference on Advances in Computer Entertainment Technology, ACE 2011, Lisbon, Portugal, ACM New York, NY, USA (2011) 1–18

16. Passyn, K., Sujan, M.: Skill-based versus effort-based task difficulty: A task-analysis approach to the role of specific emotions in motivating difficult actions. Journal of Consumer Psychology **22**(3) (2012) 461–468
17. Levieux, G.: Mesure de la difficulté dans les jeux vidéo. Thèse, Conservatoire National des Arts et Métiers CNAM Paris (2011)
18. Hunicke, R., LeBlanc, M., Zubeck, R.: MDA: A Formal Approach to Game Design and Game Research. In: Proceedings of the AAAI Workshop on Challenges in Game AI, San Jose, CA, USA, AAAI Press (2004)
19. Delignières, D., Famose, J.: Perception de la difficulté et nature de la tâche. Science et motricité **23** (1994) 39–47
20. Borg, G., Bratfisch, O., Dorni'c, S.: On the problems of perceived difficulty. Scandinavian journal of psychology **12**(1) (1971) 249–260
21. Slifkin, A.B., Grilli, S.M.: Aiming for the future: prospective action difficulty, prescribed difficulty, and fitts law. Experimental Brain Research **174**(4) (2006) 746–753
22. Delignières, D., Famose, J.P.: Perception de la difficulté, entropie et performance. Science & sports **7**(4) (1992) 245–252
23. Delignières, D., Famose, J.P., Genty, J.: Validation d'une échelle de catégories pour la perception de la difficulté. Revue STAPS **34** (1994) 77–88
24. Delignières, D., Famose, J.P., Thépaut-Mathieu, C., Fleurance, P., et al.: A psychophysical study of difficulty rating in rock climbing. International Journal of Sport Psychology **24** (1993) 404–404
25. Delignières, D., Brisswalter, J., Legros, P.: Influence of physical exercise on choice reaction time in sports experts: the mediating role of resource allocation. Journal of Human Movement Studies **27**(4) (1994) 173–188
26. Fitts, P.M.: The information capacity of the human motor system in controlling the amplitude of movement. Journal of experimental psychology **47**(6) (1954) 381
27. Kahneman, D., Frederick, S.: A model of heuristic judgment. In Holyoak, K.J., Morrison, R.G., eds.: The Cambridge Handbook of Thinking and Reasoning. 1 edn. Cambridge University Press, Cambridge, UK (2005) 267–293
28. Shah, A.K., Oppenheimer, D.M.: Heuristics made easy: an effort-reduction framework. Psychological bulletin **134**(2) (mar 2008) 207–22
29. Kahneman, D., Tversky, A.: Judgment under Uncertainty: Heuristics and Biases. Science (New York, N.Y.) **185**(4157) (sep 1974) 1124–31
30. Russo, J.E., Schoemaker, P.J.H.: Managing overconfidence. Sloan Management Review **33**(2) (1992) 7–17
31. Bessière, V.: Excès de confiance des dirigeants et décisions financières: une synthèse. Finance Contrôle Stratégie **10** (2007) 39–66
32. Moore, D.A., Healy, P.J.: The Trouble with Overconfidence. Psychological review **115**(2) (apr 2008) 502–17
33. Griffin, D., Tversky, A.: The weighing of evidence and the determinants of confidence. Cognitive psychology **411435** (1992) 411–435
34. Johnson, D.D.P., Fowler, J.H.: The evolution of overconfidence. Nature **477**(7364) (sep 2011) 317–20
35. Bandura, A.: Self-efficacy: Toward a Unifying Theory of Behavioral Change. Psychological Review **84**(2) (1977) 191–215
36. Keren, G.: Facing uncertainty in the game of bridge: A calibration study. Organizational Behavior and Human Decision Processes **39**(1) (feb 1987) 98–114
37. Linnet, J., Gebauer, L., Shaffer, H., Mouridsen, K., Møller, A.: Experienced poker players differ from inexperienced poker players in estimation bias and decision bias. Journal of Gambling Issues (24) (2010) 86–100

38. Park, Y.J., Santos-Pinto, L.: Overconfidence in tournaments: Evidence from the field. Theory and Decision **69**(1) (2010) 143–166
39. Sundali, J., Croson, R.: Biases in casino betting : The hot hand and the gambler ' s fallacy. Judgment and Decision Making **1**(1) (2006) 1–12
40. Parke, J., Griffiths, M.: The psychology of the fruit machine: The role of structural characteristics (revisited). International Journal of Mental Health and Addiction **4**(2) (2006) 151–179
41. Lichtenstein, S., Fischhoff, B.: Do those who know more also know more about how much they know? Organizational Behavior and Human Performance **20** (1977) 159–183
42. Klayman, J., Soll, J.B.: Overconfidence: It depends on how, what, and whom you ask. Organizational Behavior and Human Decision Processes **79**(3) (1999) 216–247
43. Kahneman, D., Tversky, A.: Subjective probability: A judgment of representativeness. Cognitive Psychology **3**(3) (1972) 430–454
44. Croson, R., Sundali, J.: The gambler's fallacy and the hot hand: Empirical data from casinos. Journal of Risk and Uncertainty **30**(3) (2005) 195–209
45. Gilovich, T., Vallone, R., Tversky, A.: The hot hand in basketball: On the misperception of random sequences. Cognitive Psychology **17**(3) (jul 1985) 295–314
46. Langer, E.J.: The illusion of control. Journal of personality and social psychology **32**(2) (1975) 311–328
47. Goodie, A.S.: The role of perceived control and overconfidence in pathological gambling. Journal of Gambling Studies **21**(4) (2005) 481–502
48. Pulford, B.D., Colman, A.M.: Overconfidence: Feedback and item difficulty effects. Personality and Individual Differences **23**(1) (jul 1997) 125–133
49. Costikyan, G.: Uncertainty in Games. 1 edn. MIT Press, Cambridge, USA (2013)
50. Lankoski, P., Björk, S.: Game Research Methods: An Overview. 1 edn. ETC Press (2015)
51. Bates, D., Mächler, M., Bolker, B.M., Walker, S.C.: Fitting linear mixed-effects models using lme4. Journal of Statistical Software **67**(1) (2015) 1–48
52. Chen, G., Gully, S.M., Eden, D.: Validation of a New General Self-Efficacy Scale. Organizational Research Methods **4**(1) (2001) 62–83
53. Bandura, A.: Guide for constructing self-efficacy scales. In Urdan, T., Pajares, F., eds.: Self-efficacy beliefs of adolescents. 1 edn. Information Age Publishing, Charlotte, USA (2006) 307–337
54. Holt, C.A., Laury, S.K.: Risk aversion and incentive effects. The American Economic Review **92**(5) (2002) 1644–1655
55. Nakagawa, S., Schielzeth, H.: A general and simple method for obtaining r2 from generalized linear mixed-effects models. Methods in Ecology and Evolution **4**(2) (2013) 133–142
56. Keren, G.: On The Calibration of Probability Judgments: Some Critical Comments and Alternative Perspectives. Journal of Behavioral Decision Making **10**(3) (sep 1997) 269–278
57. Barber, B.M., Odean, T.: Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics **116**(1) (2001) 261–292
58. Stone, D.N.: Overconfidence in Initial Self-Efficacy Judgments: Effects on Decision Processes and Performance. Organizational Behavior and Human Decision Processes **59**(3) (1994) 452–474
59. Caillois, R.: Les jeux et les hommes : le masque et le vertige. 2 edn. Gallimard, Paris, France (1958)

60. Arkes, H.R., Christensen, C., Lai, C., Blumer, C.: Two methods of reducing overconfidence. Organizational Behavior and Human Decision Processes **39** (1987) 133–144
61. Goldberg, J.H., Kotval, X.: Computer interface evaluation using eye movements : Methods and constructs Computer interface evaluation using eye movements : methods and constructs. International Journal of Industrial Ergonomics **24**(November 2015) (1999) 631–645
62. Klingner, J., Tversky, B., Hanrahan, P.: Effects of visual and verbal presentation on cognitive load in vigiolance, memory, and arithmetic tasks. Psychophysiology **48** (2011) 323–332