Not Every Moment is a Boss Fight — Affordance-Level Modeling of Attentional Structure in Games via Physiological Arousal

Natali Rein
Institute of Psychology
Rheinisch-Westfälische Technische Hochschule
Aachen, Germany
nattnpc@gmail.com

Thomas Günther
Department of Psychological Assessment and Intervention
Rheinisch-Westfälische Technische Hochschule
Aachen, NRW, Germany
guenther@psych.rwth-aachen.de

Abstract

Physiological measures are increasingly used to study player experience during play, but they are hard to interpret: interactive systems are complex, and it is tempting to read subjective states directly off a signal. This paper takes an exploratory approach to a narrower question — how a game's design structure shapes physiological arousal. We introduce *affordance-level attentional structure* as a unit of analysis: rather than treating arousal as a label for emotion, we ask how recurring, designer-controlled gameplay affordances — interaction, combat, reward, pacing, decision-making, and so on — jointly relate to a player's overall arousal. Using electrodermal activity (EDA) recorded from players of two structurally distinct games, an action-driven shooter (Destiny 2) and a narrative-driven interactive drama (Detroit: Become Human), we use ridge regression as an interpretable analytic lens, not a predictive tool, to estimate the relative contribution of each affordance when affordances are correlated. The resulting contribution patterns differ substantially from what simple descriptive statistics recover (Spearman $\rho \approx -0.20$ and 0.02 across the two games), and within each game the dominant affordances are stable across players, suggesting consistent attentional structures. Because the sample is small and annotation relied on a single coder, we present these patterns as exploratory structural tendencies rather than general claims. Our aim is to show how interpretable, regularized modeling can support theory-driven analysis of player experience while avoiding reductive mappings from physiological signals to emotion labels.

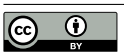
CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**.

Keywords

player experience, attention, electrodermal activity, physiological computing, gameplay affordances, ridge regression, attentional structure

ACM Reference Format:
Natali Rein and Thomas Günther. 2026. Not Every Moment is a Boss Fight — Affordance-Level Modeling of Attentional Structure in Games via Physiological Arousal. In *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY Companion '26), November 02–05, 2026, York, United Kingdom.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3800965.3834281



This work is licensed under a Creative Commons Attribution 4.0 International License.
CHI PLAY Companion '26, York, United Kingdom
© 2026 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-2565-4/26/11
https://doi.org/10.1145/3800965.3834281

1 Introduction

Digital games are interactive, temporally unfolding systems that continuously demand perceptual, cognitive, and motor resources from players. Understanding how specific design choices organize these demands, and how attentional structure emerges from the interplay of design affordances, is a central challenge in player experience research.

Physiological measures have become an established tool for studying player experience dynamics. A substantial body of work at CHI and CHI PLAY has demonstrated that signals such as electrodermal activity (EDA) and heart rate provide temporally continuous access to aspects of experience that retrospective self-report cannot capture [9, 17, 20, 22]. Complementary work on biometric storyboards showed how physiological data can be integrated into games user research workflows [21]. Across this body of work, a consistent interpretive constraint applies: physiological signals do not encode discrete emotional states, their meaning is context-dependent, and the relationship between signal and experience is many-to-one [5, 10].

What remains less developed is how physiological data can be analyzed at the level of game design structure rather than at the level of individual events or aggregate session means. Prior work has largely examined physiological responses to specific gameplay moments, or correlated overall physiological measures with self-report [9, 17]. These approaches yield important insights but do not directly address how multiple design elements jointly organize attentional demand across a play session.

This paper addresses that gap. We treat gameplay in terms of gameplay affordances, recurring, designer-controlled categories of interaction, narrative structure, or challenge that afford opportunities for player action and cognitive engagement [1, 6, 15], and examine how affordance-level EDA responses jointly shape each player's overall arousal profile. Using ridge regression as an analytic lens rather than a predictive tool, we demonstrate that this approach reveals stable, design-relevant attentional structures that differ systematically between an action-driven and a narrative-driven game, and that cannot be recovered from simpler descriptive statistics. This work is positioned as a first paper in a broader research program; findings are offered as exploratory observations that motivate further investigation.

2 Background

Attention and arousal. Attention has been conceptualized as a distributed, context-sensitive process shaped by task structure, temporal constraints, and interaction design [7, 16, 24]. Physiological arousal modulates the conditions under which attention operates rather than constituting attention itself [16, 18]. EDA indexes sympathetic arousal without encoding emotional valence or specifying cognitive meaning; interpretation requires careful grounding in the interactive context in which responses occur [3–5].

Physiological measures in games research. Prior physiological games research has established reliable links between EDA, heart rate, and aspects of player experience [9, 20], demonstrated how biofeedback can be integrated into game interaction [22], and developed workflows for aligning physiological signals with gameplay events [21]. Research on action video games has further shown that gameplay shapes the spatial distribution of visuospatial attention over time [11]. Across this work, a consistent methodological stance has emerged: physiological measures are most informative when embedded in a theoretically grounded analytic framework rather than used for automated classification [10].

Modeling player experience. Predictive modeling has been introduced in games research primarily for behavioral outcomes such as retention and churn [12], with an emphasis on accuracy over interpretability. Recent work in HCI and physiological computing has argued for interpretable, regularized approaches suited to small-sample, theory-driven contexts [2, 10]. Core task analysis frameworks for gameplay [14] provide a complementary perspective that informs the affordance-level operationalization adopted here. Despite this potential, predictive modeling remains underutilized as an analytic lens for examining player experience at the level of game design.

3 Method

3.1 Study Design and Participants

Data were collected from $N = 20$ participants (10 per game), ages 18–33 years ($M = 20.75$), of whom 40% were female-identified and 60% were male-identified. Five players per game were experienced genre players and five were target audience members with limited prior experience. All participants were tested individually in a semi-naturalistic living room setting. Each session lasted approximately 1.5 hours. Participants provided informed consent and were fully debriefed at the session's conclusion.

Two commercially released AAA games with contrasting design structures were selected: an action-driven multiplayer shooter (Destiny 2) and a narrative-driven interactive drama (Detroit: Become Human). Models were estimated separately for each game; the cross-game comparison in Section 4.3 is qualitative and descriptive rather than inferential.

3.2 EDA Recording and Normalization

EDA was recorded continuously using a BIOPAC MP150 system with PPGED-R module at 2000 samples per second. Ag/AgCl electrodes were placed at the thenar and hypothenar eminences of the non-dominant palm following standard placement guidelines [3, 4]. A baseline period of at least two minutes was observed before gameplay. EDA signals were normalized per participant using a min-max procedure [19, 20]:

$$\mathrm{EDA}_{\mathrm{norm}} = \frac{\mathrm{EDA}(t) - \mathrm{EDA}_{\mathrm{min}}}{\mathrm{EDA}_{\mathrm{max}} - \mathrm{EDA}_{\mathrm{min}}} \times 100, \tag{1}$$

where $\mathrm{EDA}(t)$ is the participant's skin conductance level at time t, and $\mathrm{EDA}_{\mathrm{min}}$ and $\mathrm{EDA}_{\mathrm{max}}$ are the session-wide minimum and maximum values.

Because skin conductance carries large between-participant differences unrelated to gameplay, resting level, skin properties, electrode contact, raw response amplitudes are not directly comparable across players. This per-participant range correction rescales each player's responses to a common 0–100 scale, removing individual-baseline differences while preserving the relative magnitude of each player's responses [19], so that a given affordance's response can be compared across the ten players of a game. Normalization was applied to the continuous conductance trace prior to response extraction (Section 3.3), so that all subsequent response amplitudes are expressed on this common within-participant scale.

Signal processing. The raw skin conductance signal was analyzed without additional filtering or downsampling. Responses affected by motion artifacts arising from hand movement during gameplay were identified and excluded by visual inspection prior to response scoring.

Recording conditions. Sessions were conducted in an air-conditioned room maintained at approximately 22 °C. Skin temperature was not separately recorded, which we note as a limitation.

3.3 Affordance Annotation and Response Extraction

Gameplay affordances were identified through a theory-driven process consistent with core task analysis approaches to gameplay [14], operationalized at an intermediate level of abstraction — recurring, design-relevant gameplay structures rather than fine-grained micro-events [1, 15]. Tables 1 and 2 describe all coded affordances per respective game.

Affordances were annotated live by the first author during each play session. As each affordance occurred, its onset was marked directly onto the participant's EDA recording in real time, so that annotation and physiological signal shared a single timeline; no post-hoc synchronization between gameplay video and the EDA stream was required. Where affordances co-occurred (for example, combat during environmental traversal, or a quick-time event within a transition scene), the segment was labeled with the affordance that was active and foregrounded at that instant. Annotation was single-pass: markers were placed as events unfolded rather than re-coded from recorded video, which introduces a small marking latency and no opportunity for post-hoc correction. A single coder performed all annotation and inter-rater reliability was not assessed, which we acknowledge as the principal limitation of this work (Section 5.2).

For each affordance, the response was scored as the peak amplitude of the first skin conductance response (SCR) that met the criteria of Dawson, Schell, and Filion [8]: onset falling 1–3 s after the affordance marker, with amplitude exceeding the standard threshold. Where the first occurrence of an affordance did not elicit a qualifying SCR, the next occurrence meeting the criteria was used;

Table 1: Coded gameplay affordances for Destiny 2.

#	Affordance	Description
1.	Interaction	Continuous player input requiring sensorimotor coordination, including navigation, aiming, and moment-to-moment control.
2.	Combat	Active enemy engagement requiring sustained attention and rapid motor response.
3.	Boss Fight	High-stakes combat with named enemies, elevated failure consequences, and distinct attack patterns.
4.	Loot Box	Reward containers requiring evaluation of earned items; associated with anticipatory uncertainty.
5.	Gear	Equipment and loadout decisions; armor, weapons, vehicles, and cosmetics classified from common to exotic, motivating ongoing progression.
6.	Enemies	Enemy presence scored at the onset of engagement; in a shooter, presence and engagement are near-simultaneous, so this category indexes the initial threat-response moment.
7.	Sudden Deaths	Unexpected player failure states, narratively justified through resurrection by the player's Ghost AI companion, which may prompt renewed attentional focus.
8.	Socializing	Interaction with other players in shared game spaces.
9.	Environment	Spatial exploration and navigation, including entry into new areas requiring assessment of unfamiliar surroundings.
10.	Music	Prominent non-diegetic audio foregrounded in the gameplay experience.
11.	Cinematics	Non-interactive cutscenes presenting narrative or contextual information.
12.	Objective Complete	Mission completion notifications and reward acknowledgment screens.
13.	Character	Character selection, customization, and progression screens.

Table 2: Coded gameplay affordances for Detroit: Become Human.

#	Affordance	Description
1.	Interaction	Player input within scenes including object examination, clue discovery, and scene navigation.
2.	Quick Time Events	Time-constrained button prompts requiring rapid response under pressure, often with narrative consequences.
3.	Transition Scene	Non-interactive or minimally interactive narrative segments connecting gameplay moments and reorienting attention.
4.	Decision Making	Branching narrative choice points with perceived story consequences for characters.
5.	Environment	Spatial exploration of scene environments and discovery of contextual narrative information.
6.	Characters	Character-focused narrative scenes emphasizing dialogue, relationship dynamics, and emotional content.
7.	Music	Non-diegetic audio foregrounded during narrative or emotionally significant scenes.
8.	Timelines	Post-chapter visualizations of branching narrative paths and outcomes across the story.
9.	Reprogramming	Sequences in which android characters rewrite their own core coding, signalled by a colored LED on the temple; encountered early without direct explanation.
10.	Breaking the Wall	Moments in which player decisions free android characters from programming constraints, foregrounding the weight of player agency.
11.	Outcomes	Consequence displays showing the result of player decisions; an extension of decision making in which anticipated actions become visible outcomes.
12.	Visuals/Cinematics	Non-interactive cinematic sequences presenting story content; analogous to watching a film segment within the interactive drama.

where no occurrence met the criteria for a given player, no value was recorded for that affordance–player pair. SCRs were identified and scored manually against these criteria; automated scoring was not used. These values were assembled into a player × affordance matrix per game.

A cell was left empty where a player did not encounter a given affordance during their session. Empty cells accounted for 10 of 130 values in Destiny 2 (falling chiefly on objective completions, which not all players reached) and 4 of 120 in Detroit: Become Human (chiefly the scripted "breaking the wall" beat). Handling of these cells is described in Section 3.4.

3.4 Ridge Regression and Cross-Validation

A composite target variable y was constructed for each participant as the row-wise mean of their normalized affordance-level values, representing a player-specific overall arousal profile. Ridge regression was then used as a regularized attribution mechanism to estimate stable relative contribution weights across affordances:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \left(\|\mathrm{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda \|\boldsymbol{\beta}\|_2^2 \right) \tag{2}$$

Intuitively, the target y summarizes how physiologically aroused each player tended to be overall — their average normalized arousal across affordance categories. The ridge coefficients then express

how strongly each affordance's arousal moves *with* that overall profile once all affordances are considered jointly and correlated affordances are prevented from inflating one another. A larger positive coefficient means a player's arousal during that affordance tracks more closely with their overall arousal level, i.e., that affordance is a stronger relative marker of where sustained, arousal-linked attention concentrates. Coefficients are relative, regularized attribution weights, not effect sizes in physical units.

The L2 penalty stabilizes coefficient estimates under correlated affordances, preserving all affordances in the model. $\lambda = 1.0$ was held constant across folds; a sensitivity analysis confirmed rank ordering is stable across $\lambda = 0.1$ to 10.0. We acknowledge that defining y as a function of $\mathbf{X}$ raises circularity concerns, and we use ridge strictly as an attribution and structure-finding lens rather than a predictive claim. To confirm it recovers structure that simple descriptives miss, Spearman rank correlations between ridge rankings and simple mean-deviation rankings were $\rho = -0.20$ (Destiny 2) and $\rho = 0.02$ (Detroit: Become Human) — near zero.

Leave-one-player-out cross-validation (LOPO-CV) was used to assess coefficient stability. Missing affordance values (Section 3.3) were mean-imputed using scikit-learn's `SimpleImputer` within each training fold only, so that imputed values never drew on held-out data; standardization was likewise fit within training folds only to prevent leakage. All analyses were conducted in Python 3 using scikit-learn, pandas, numpy, and scipy.

4 Results

Results are presented separately per game. All coefficients are positive and fall within a narrow absolute range, and cross-validation error bars overlap for adjacently ranked affordances; the interpretable signal therefore lies in the broad tiering — which affordances sit clearly at the top versus the bottom of each game's distribution — rather than in fine distinctions between neighbours. Differences between adjacent affordances are not accompanied by formal statistical tests. Interpretations are exploratory and descriptive, reflecting tentative structural tendencies within a small sample. One affordance warrants explicit caution: *objective complete* in Destiny 2 was present for only four of ten players, so its coefficient rests largely on imputed values and should not be read as a solid result.

4.1 Destiny 2: Action-Driven Attentional Structure

Figure 1 shows standardized ridge regression coefficients for Destiny 2 (β range = 0.0048–0.0210; SD range = 0.0013–0.0036). The coefficient distribution reveals a clear hierarchy consistent with the action-driven design of this title. Interaction exhibits the largest contribution ($\beta = 0.0210$, SD = 0.0013), consistent with the sustained perceptual–motor demands of action-oriented gameplay. That interaction dominates even when modeled alongside high-intensity affordances such as boss fights and combat underscores that moment-to-moment sensorimotor engagement, rather than discrete high-stakes encounters, is the primary driver of arousal-linked attention in this design context.

Reward-related affordances follow closely: loot box ($\beta = 0.0160$, SD = 0.0036) and gear ($\beta = 0.0146$, SD = 0.0023) rank second and third, suggesting that evaluative uncertainty and progression mechanics contribute substantially. Boss fight ($\beta = 0.0124$, SD = 0.0027) and combat ($\beta = 0.0117$, SD = 0.0020) show elevated contributions during performance-critical situations. At the lower end, cinematics shows the weakest contribution ($\beta = 0.0048$, SD = 0.0030), indicating that passive narrative content exerts minimal influence on sustained arousal when modeled alongside action-oriented affordances.

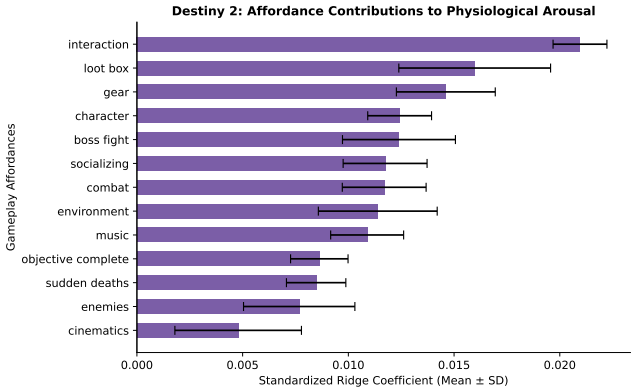


Figure 1: Standardized ridge regression coefficients for Destiny 2. Error bars indicate cross-validation variability.

4.2 Detroit: Become Human: Narrative-Driven Attentional Structure

Figure 2 shows coefficients for Detroit: Become Human (β range = 0.0033–0.0188; SD range = 0.0016–0.0030). In contrast to Destiny 2, the coefficient distribution reflects a narrative-driven attentional structure shaped by pacing and time-critical interaction rather than continuous motor engagement.

Interaction remains the strongest contributor ($\beta = 0.0188$, SD = 0.0021), though at a lower absolute magnitude than in Destiny 2. Quick time events ($\beta = 0.0153$, SD = 0.0017) and transition scenes ($\beta = 0.0141$, SD = 0.0023) emerge as comparably strong contributors. Transition scenes — non-interactive segments that connect gameplay moments and reorient attention — rank among the top three affordances, suggesting that narrative pacing itself carries attentional weight independent of direct player action. Characters ($\beta = 0.0131$, SD = 0.0020) and environment ($\beta = 0.0106$, SD = 0.0029) show moderate contributions. Notably, decision making shows one of the lowest coefficients ($\beta = 0.0037$, SD = 0.0030) despite its narrative importance, consistent with accounts distinguishing reflective deliberation from autonomic arousal [10, 23]. Visuals/cinematics contributes minimally ($\beta = 0.0035$, SD = 0.0026), mirroring the low contribution of cinematics in Destiny 2.

4.3 Cross-Game Comparison

Across both games, interaction-related affordances rank highest, suggesting that player input demands are consistently associated with the strongest arousal-linked contributions regardless of design context. Reward- and performance-oriented affordances (loot box, boss fight) dominate in Destiny 2 with no analogues in Detroit.

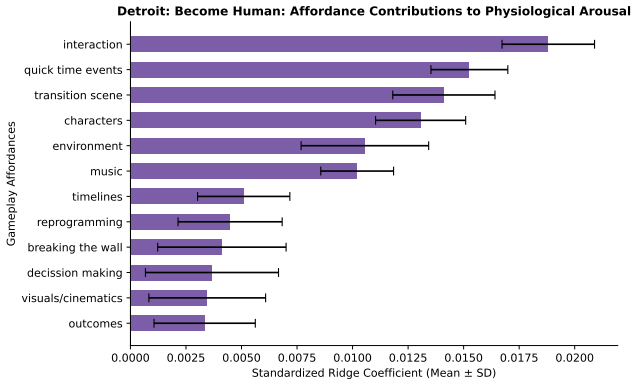


Figure 2: Standardized ridge regression coefficients for Detroit: Become Human. Error bars indicate cross-validation variability.

Pacing-related affordances (transition scene, quick time events) are prominent in Detroit but absent in Destiny 2. Cinematics and visuals show low coefficients in both games despite their aesthetic salience, suggesting that passive audiovisual content contributes minimally to physiological arousal once action and pacing demands are accounted for.

5 Discussion and Future Work

This paper introduced affordance-level attentional structure as a unit of analysis and demonstrated that ridge regression reveals design-relevant contribution patterns not recoverable from simpler descriptive approaches. In the present data, interaction-related affordances consistently dominate arousal-linked attention across both design contexts, while narrative and cinematic content contributes minimally in the absence of action demands. These findings tentatively suggest that physiological arousal during play may be more strongly shaped by the requirement to act under constraint than by content presence alone — a hypothesis warranting investigation in larger and more diverse samples.

5.1 Design Implications

Although the present findings are exploratory, they offer preliminary diagnostic insights relevant to game design practice. Designers routinely reason about attentional load, pacing, and cognitive demand during playtesting and iteration [13]. The present approach provides a complementary empirical lens for examining how these intuitions manifest in physiological data across players. Three tentative observations are worth highlighting. First, the dominance of interaction across both games suggests that player input demands are the primary driver of arousal-linked attention regardless of design context. Adjusting interaction frequency and intensity may therefore affect attentional load more than altering narrative or audiovisual content alone. Second, the prominence of reward-related affordances in Destiny 2 (loot box, gear) suggests that evaluative uncertainty and progression mechanics contribute meaningfully to sustained physiological engagement.

The result we find most provocative is the low contribution of decision making in Detroit: Become Human, one of the weakest coefficients in the game, despite these being the moments players deliberate over most consciously. Read against the rest of the distribution, this is coherent rather than paradoxical. The affordances that rank highest across both games, interaction, quick-time events, transition pacing, combat, share a demand to act under time or input constraint, whereas branching choices in Detroit are typically self-paced and low in acute time pressure. Notably, outcomes (the resolution of those choices) also rank low, so the arousal is located neither in the deliberation nor in its reveal, but in constrained action itself. This converges with accounts distinguishing reflective, effortful cognition from autonomic sympathetic activation [10, 23]: a choice can be experientially central yet autonomically quiet.

Two readings follow, and we hold them jointly pending further data. First, EDA may simply be the wrong instrument for reflective significance — the "meaningful choice" experience may live in cognitive load, valence, or memory rather than in sympathetic arousal. Second, our session-level modeling may average away brief phasic responses within long deliberation segments; temporally resolved modeling could recover within-segment responses that a summary obscures. Either way, the open question — what is the physiological signature of meaningful choice? — is one we see as rich enough to anchor a dedicated study pairing self-report and multimodal measures with choice-level annotation, and we would welcome the community's input on how to operationalize it.

5.2 Limitations and Future Work

Because affordance categories are the backbone of the analysis, all reported structure is conditional on the annotation scheme, and single-coder annotation is the most consequential limitation of this work. We therefore treat the contribution patterns as exploratory structural tendencies rather than established findings. Formal inter-rater reliability is a priority for the next stage: multi-coder annotation with reported agreement is one of our stated future directions, and the taxonomies in Tables 1 and 2 are provided in full precisely so that their reproducibility can be tested by other researchers.

Two further scope conditions apply. Because each affordance was anchored to its first qualifying occurrence, the affordance-level values index players' initial response to each affordance rather than a session-averaged level; given habituation, repeated encounters would be expected to elicit smaller responses. And the sample size of $N = 10$ per game, while consistent with common practice in physiological player experience research [9, 17], means the present findings should be treated as structural tendencies rather than generalizable mappings.

This work is the first paper in a broader research program. Future directions include: (1) extending to temporally resolved modeling to examine how attentional structures evolve during play; (2) incorporating multimodal physiological measures to disentangle attentional, affective, and cognitive processes; (3) applying multi-coder annotation with formal reliability assessment; and (4) replicating across a broader range of games and player populations to assess generalizability of affordance-level attentional structures.

References

[1] Hamna Aslam and Joseph Alexander Brown. 2022. *Affordance Theory in Game Design.* Springer. doi:10.1007/978-3-031-02123-7

[2] Gagan Bansal, Tongshuang Wu, Joyce Zhou, Raymond Fok, Besmira Nushi, Ece Kamar, Marco Tulio Ribeiro, and Daniel Weld. 2021. Does the Whole Exceed Its Parts? The Effect of AI Explanations on Complementary Team Performance. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems.* ACM, 1–16. doi:10.1145/3411764.3445717

[3] Wolfram Boucsein. 2012. *Electrodermal Activity* (2nd ed.). Springer. doi:10.1007/978-1-4614-1126-0

[4] Jason J. Braithwaite, Derrick G. Watson, Robert Jones, and Mickey Rowe. 2013. *A Guide for Analysing Electrodermal Activity (EDA) and Skin Conductance Responses (SCRs) for Psychological Experiments.* Technical Report. University of Birmingham.

[5] John T. Cacioppo, Louis G. Tassinary, and Gary G. Berntson (Eds.). 2007. *Handbook of Psychophysiology* (3rd ed.). Cambridge University Press.

[6] Rogelio E. Cardona-Rivera and R. Michael Young. 2014. A Cognitivist Theory of Affordances for Games. In *Proceedings of DiGRA 2013.* doi:10.26503/dl.v2013i1.687

[7] Maurizio Corbetta and Gordon L. Shulman. 2002. Control of Goal-Directed and Stimulus-Driven Attention in the Brain. *Nature Reviews Neuroscience* 3, 3 (2002), 201–215. doi:10.1038/nrn755

[8] Michael E. Dawson, Anna M. Schell, and Diane L. Filion. 2007. The Electrodermal System. In *Handbook of Psychophysiology* (3rd ed.), John T. Cacioppo, Louis G. Tassinary, and Gary G. Berntson (Eds.). Cambridge University Press, 159–181. doi:10.1017/CBO9780511546396.007

[9] Anders Drachen, Lennart E. Nacke, Georgios Yannakakis, and Anja Lee Pedersen. 2010. Correlation Between Heart Rate, Electrodermal Activity and Player Experience in First-Person Shooter Games. In *Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games.* 49–54. doi:10.1145/1836135.1836143

[10] Stephen H. Fairclough. 2009. Fundamentals of Physiological Computing. *Interacting with Computers* 21 (2009), 133–145. doi:doi:10.1016/j.intcom.2008.10.011

[11] C. Shawn Green and Daphne Bavelier. 2006. Effect of Action Video Games on the Spatial Distribution of Visuospatial Attention. *Journal of Experimental Psychology: Human Perception and Performance* 32, 6 (2006), 1465–1478. doi:10.1037/0096-1523.32.6.1465

[12] Fabian Hadiji, Rafet Sifa, Anders Drachen, Christian Thurau, Kristian Kersting, and Christian Bauckhage. 2014. Predicting Player Churn in the Wild. In *2014 IEEE Conference on Computational Intelligence and Games (CIG).* IEEE, 1–8. doi:10.1109/CIG.2014.6932876

[13] Celia Hodent. 2020. *The Psychology of Video Games.* CRC Press.

[14] Bjorn Ingo Hougaard and Hendrik Knoche. 2024. Aiming, Pointing, Steering: A Core Task Analysis Framework for Gameplay. *Proceedings of the ACM on Human-Computer Interaction* 8, CHI PLAY (2024), 1–48. doi:10.1145/3677057

[15] Robin Hunicke, Marc LeBlanc, and Robert Zubek. 2004. MDA: A Formal Approach to Game Design and Game Research. In *Proceedings of the AAAI Workshop on Challenges in Game AI (GDC 2004).*

[16] Daniel Kahneman. 1973. *Attention and Effort.* Prentice Hall.

[17] J. Matias Kivikangas, Guillaume Chanel, Ben Cowley, Inger Ekman, Mikko Salminen, Simo Järvelä, and Niklas Ravaja. 2011. A Review of the Use of Psychophysiological Methods in Game Research. *Journal of Gaming and Virtual Worlds* 3, 3 (2011), 181–199. doi:10.1386/jgvw.3.3.181_1

[18] Annie Lang. 1995. The Limited Capacity Model of Mediated Message Processing. *Journal of Communication* 45, 3 (1995), 46–70.

[19] David T. Lykken, Robert Rose, Bertrand Luther, and Melvin Maley. 1966. Correcting Psychophysiological Measures for Individual Differences in Range. *Psychological Bulletin* 66, 6 (1966), 481–484.

[20] Rosalind L. Mandryk and M. Stella Atkins. 2007. A Fuzzy Physiological Approach for Continuously Modeling Emotion During Interaction with Play Technologies. *International Journal of Human-Computer Studies* 65, 4 (2007), 329–347. doi:doi:10.1016/j.ijhcs.2006.11.011

[21] Pejman Mirza-Babaei, Lennart E. Nacke, John Gregory, Nigel Collins, and Geraldine Fitzpatrick. 2013. How Does It Play Better? Exploring User Testing and Biometric Storyboards in Games User Research. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 1499–1508. doi:10.1145/2470654.2466200

[22] Lennart E. Nacke, Michael Kalyn, Calvin Lough, and Rosalind L. Mandryk. 2011. Biofeedback Game Design: Using Direct and Indirect Physiological Control to Enhance Game Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* 103–112. doi:10.1145/1978942.197895

[23] Steven E. Petersen and Michael I. Posner. 2012. The Attention System of the Human Brain: 20 Years After. *Annual Review of Neuroscience* 35 (2012), 73–89. doi:10.1146/annurev-neuro-062111-150525

[24] Cynthia Rudin, Chaofan Chen, Zhi Chen, Haiyang Huang, Lesia Semenova, and Chudi Zhong. 2022. Interpretable Machine Learning: Fundamental Principles and 10 Grand Challenges. *Statistics Surveys* 16 (2022), 1–85. doi:10.48550/arXiv.2103.11251