

A Primer on Data-Driven Gamification Design

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Abstract

Gamification gradually gains more attention. However, gamification and its successful application is still unclear. There is a lack of insights and theory on the relationships between game design elements, motivation, domain context and user behavior. We want to discover the potentials of data-driven optimization of gamification design, e.g. by the application of machine learning techniques on user interaction data. Therefore, we propose data-driven gamification design (DDGD) and conducted a questionnaire with 17 gamification experts. Our results show that respondents regard DDGD as a promising method to improve gamification design and lead to a general definition for DDGD.

1 Introduction

Gamification has been a hot topic for some time now and gained attention of academics and practitioners alike. Previous work has focused mainly on models from psychology, user tests and personal experiences [Yee16, Yee07, HT14a, KH14, Dix11]. In a more and more data-driven world, new possibilities emerge to replace previously manually created models with

machine-made ones. Recent research indicates that instead of using only predefining player types to select or assign game design elements a data-driven gamification design approach (DDGD) [HT14b, HHS14, Det15, JXKV16, SBSH16, OND17], which would allow us to learn the assignments on collected real user behavioral data, could improve gamification design. One advantage would be that the selection and implementation of game design elements or motivational affordances could be adapted in real-time. Finally, based on live interactions and goals, a data-driven gamification system would automatically select the best gamification design approach. In this paper, we first introduce the data-driven gamification design (DDGD) approach. We then present a conducted questionnaire which asked leading experts in the field of Gamification about their opinion on DDGD, what impact they expect DDGD to have and what obstacles they see to successfully implement DDGD. As a result of the questionnaire we propose a general definition for data-driven gamification design. The main contributions of this paper are:

- A questionnaire collecting opinions from gamification experts on DDGD.
- The first comprehensive definition of DDGD as a new emerging topic within the field of Gamification.

The paper is structured as follows. In Section 2, we summarize the currently existing literature on DDGD. We then outline the questionnaire and highlight the process of collecting answers in Section 3. In Section 4 we analyze and discuss the results of the questionnaire and deduce a definition for DDGD. In Section 5 we

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summarize our findings and give recommendations for future work.

To our knowledge, this paper is the first work introducing DDGD as a new research field. The presented outcomes lay the foundation for a future successful adaption of DDGD.

2 Data Driven Gamification Design

Several studies on user or user type specific gamification design [HT14b, HHS14, Det15, JXKV16, SBSH16, OND17] encourage experiments with empirical data encapsulating user interactions. The main reasons for this are lacking detailed knowledge about the complexity and interdependencies of user types, motivation types, game design elements, user interface elements and actual goals of gamification. Exactly this knowledge is necessary to arrive at reliable and well-founded statements about successful gamification design. The question “Does gamification work? [...]” [HKS14] and how to make it work has remained unclear. One method to approach this is to consider well-known player typologies [HT14b] but this approach is challenging for questionnaires and interviews. The 3rd International Workshop on Gamification for Information Retrieval (GamifIR 2016) [MHKK16] assisted by Sebastian Deterding’s keynote speech “Desperately Seeking Theory: Gamification, Theory, and the Promise of a Data/AI-Driven New Science of Design”¹ [Det16] has concluded that we should take the opportunities which AI and data-driven techniques provide in order to gain deeper insights on successful gamification design.

As a result, more and more researchers have proposed data-driven approaches to gamification design. In 2013, Paharia [Pah13] suggested to use big data and gamification for customer and employee gamification. In 2014, Meder and Jain [MJ14] defined the gamification design problem and considered it as a “[...] special case of a recommendation problem for which matrix factorization constitutes a state-of-the-art solution”. In 2016, Meder et al. [MPA16] suggested a two phase procedure of gamification experiments to collect user interaction data largely avoiding negative influences such as bad usability and bugs. They further planned to apply machine learning methods to detect and learn typical interaction patterns. In 2017, Tondello et al. [TON17] likewise to Meder and Jain [MJ14] also suggested recommender systems as a solution for more personalized gamification. For all those studies an empirical evaluation of user specific gamification design is missing.

Heilbrunn et al. [HHS14, HHS17] “[...] define gamification analytics as the data-driven processes of moni-

toring and adapting gamification designs.” They evaluated seven analytics tools towards their ability to support those gamification analytics. Their findings show that no analytics tool exists which fulfills their gamification analytics requirements.

3 Questionnaire

For further insight and to learn how the research community thinks about data-driven gamification design, we conducted a questionnaire with gamification experts. As target respondents we picked authors of recently published research papers on gamification plus well known gamification experts. The survey was sent via e-mail to the selected gamification experts (N=65), which contained a link to a website where, after a brief introduction, all questions were displayed at once. Since we assumed that the concept of Data-Driven Gamification Design (DDGD) is rather unknown and not well-defined so far, we explained our understanding of DDGD in the introduction of the questionnaire as follows:

“Gamification is a hot topic for some time now and gained attention of academics and practitioners. The work carried out so far relies primarily on models from psychology, user tests and personal experiences. We argue that rather relying only on psychology theories of motivation, machine learning approaches for a data-driven gamification design approach should be used. Instead of predefining player types and matching gamification elements, DDGD allows to learn this based on collected user behavioral data. The selection and implementation of game design elements or motivational affordances can also be adapted in real-time. Based on live interactions and goals, a data-driven gamification system can select the best approach automatically.”

The questionnaire contained a mandatory part along with an optional part. The mandatory part contained eight statements regarding which respondents had to specify their level of agreement or disagreement on a five-level Likert item from “Strongly disagree” to “Strongly agree.” The statements were as follows:

1. DDGD is a known concept for me.
2. DDGD will allow for better gamification design.
3. DDGD will allow replacement of the current gamification approaches.
4. DDGD will allow for successful real-time adaption of applied game design elements.

¹slideshare.net: <https://goo.gl/YZg65N>

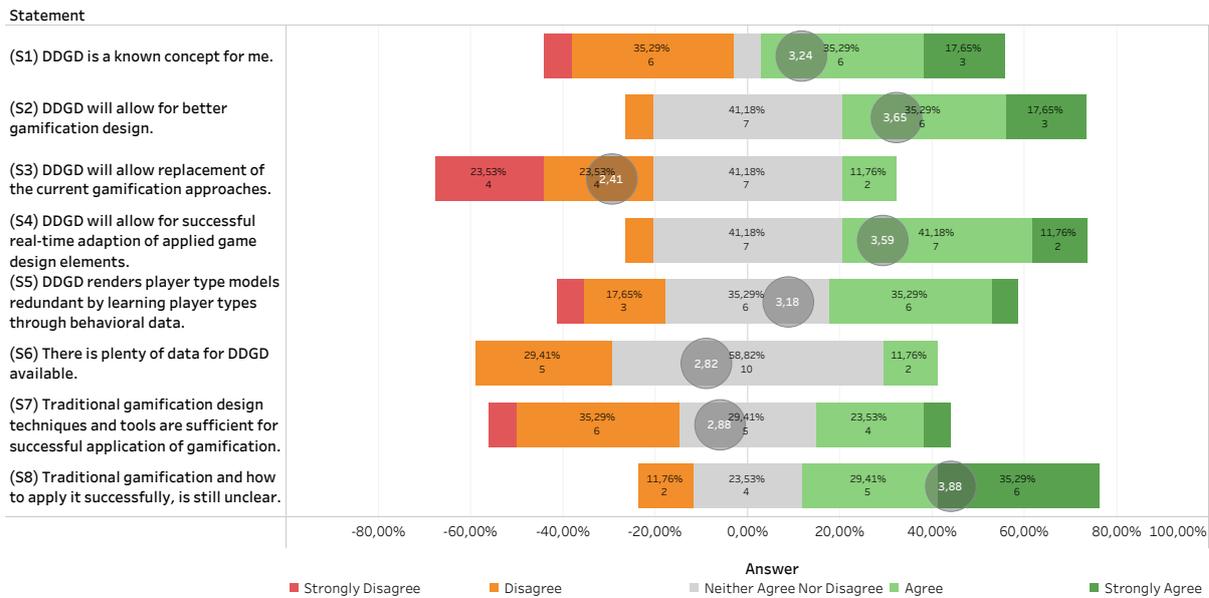


Figure 1: Distribution of the five-level Likert ratings for each statement of the mandatory part of the questionnaire. The numbers on the gray circles are the average value of all rating for each statement.

5. DDGD renders player type models redundant by learning player types through behavioral data.
6. There is plenty of data for DDGD available.
7. Traditional gamification design techniques and tools are sufficient for successful application of gamification.
8. Traditional gamification and how to apply it successfully, is still unclear.

In the optional second part, we asked for further information on how the respondents apply or plan to apply gamification, if they know any corresponding datasets or if they have other comments or suggestions.

9. Techniques or tools I use, plan to use or find promising, for the application of gamification:
 - Player and Motivation Models
 - Game or Gamification Design Frameworks (like MDA, Gamification Model Canvas, Octalysis, Six Steps To Gamification, etc.)
 - Web/App Analytics
 - User Behavior Statistics
 - Key Performance Indicators
 - Recommender Systems
 - Machine Learning
 - Artificial Intelligence
 - Other (please specify)

10. Do you know one or more gamification (user interaction) datasets? Please provide an URL if possible.
11. What kind of data in your opinion would be useful for gamification design?
12. Do you have any suggestions for data-driven gamification design approaches?
13. Comments and other suggestions:
14. Your Name
15. Agreement for publication.

- I hereby agree that my answers can be used for publication.

4 Results and Discussion

In the following, we will show how respondents answered the questionnaire. From a total of 65 invitations, to academic authors of recently published gamification papers, we have received 17 replies. Ten of them provided their full name. The responses of the participants on the mandatory part of the questionnaire are depicted in Figure 1. The ratings for the first statement (S1) show that slightly more than half (52.94%) of the respondents has an idea about data-driven gamification design (DDGD) whereas the other half seems to be uncertain. At the same time our respondents are quite optimistic about the benefits of

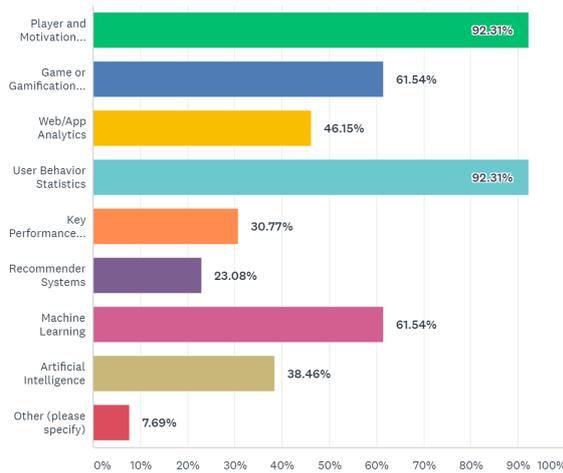


Figure 2: Distribution of respondents selections on “Techniques or tools I use, plan to use or find promising, for the application of gamification” (Q9, multiple choice question).

DDGD as merely one respondent disagrees on S2. Furthermore, respondents are rather optimistic regarding the opportunities (S2, S4, S5) of DDGD. Whereby the real-time adaption (S4) seems to be more viable to the respondents than rendering player types models redundant (S5). Thus we think, respondents are somehow skeptical about the possibility to compute something similar or even better than recent player type models from e.g. user interaction data. But the comments show that there is much hope that it will work (see below). While they are optimistic about the chances of DDGD, respondents disagree on a possible replacement of current gamification approaches by DDGD (S3). Simultaneously, respondents do not think that traditional tools and techniques are sufficient (S7) which is therefore consistent with the general optimism or even hope on DDGD (S2). In contrast, and thus a bit contradictory, the strongest agreement (64.7%) has been given to the last statement which claims that it is still unclear how to apply gamification. The prospect of low availability of data (S7) may be one reason for this. This could have dampened the optimism for DDGD as a replacement of current gamification approaches.

For the second and optional part of the questionnaire we have received 13 responses on the our questions on techniques (Q9). As depicted in Figure 2 the most common techniques for gamification design seems to be player and motivation types and statistics on user behavior closely followed by game or gamification design frameworks and machine learning. Unfortunately, as expected, no participant could provide a link to a dataset (Q10). Seven respondents submitted suggestion on the kind of data we need for DDGD (Q11). Al-

most all suggest user behavior data or data of interactions with “gamification features.” Also data on time spent (especially “time well-spent”), goals, user intentions and performances, all situational data as well as the surroundings and the context of the applied gamification have been mentioned. Further suggestions on DDGD (Q12) are like “Collect as much data as you can [...]” and that the users’ interests need a strong focus. One respondent argued that “[...] it’s important to agree on a success indicator that we can take as guidance and investigate how different data and behaviors relate to it. Without this effective DDGD will be much more difficult.” In Q13 general comments on DDGD were given. Instead of the replacement of traditional gamification design could “[...] one approach can complement the weaknesses of the others.” They further state that “[...] we might need a blend of a priori theoretical knowledge [...]” and with “[...] enough data [...]” we might be able “[...] to quickly categorize a new player [...].” Another respondent believes that psychology models are beneficial for gamification design but it is hard to successfully integrate them. The respondent is also against player type models and hopes that DDGD will be an alternative: “So while I don’t think DDGD will make Player Type models redundant — I hope it will.”

Defining *Data-Driven Gamification Design*

Taking into account previous works and the results of our questionnaire, we propose the following general definition:

Data-Driven Gamification Design (DDGD) is the automation of the gamification design process using data mining approaches to apply game design elements tailored to each individual that maximizes their expected contribution to achieve well-defined objectives.

5 Conclusion

In this paper, we have studied the opportunities of data-driven gamification design. Therefore, we have examined related work and conducted a questionnaire with 17 gamification experts to collect their expectations and suggestion for DDGD. Our findings show that, although they are slightly skeptical towards DDGD (S3, S5, S6), there is a strong demand for further solutions because it is still unclear how to apply gamification successfully (S8). Beyond that, the respondents were very optimistic that DDGD allows better gamification design (S2) but their optimism seems to be dampened by worries on available data. In the second part of the questionnaire, we collected suggestions and comments from which we derive the following recommendations for future work. We need user

behavior data or data of interactions with game design elements collected in real world studies whereby additional data like goals, user interests, time spent and general context of the applied gamification design should be considered. It would be even better if those data would be publicly available. Furthermore, researcher should find an agreement on a “success indicator” to make findings comparable and improvements measurable. Altogether, we deduced the following definition: Data-Driven Gamification Design (DDGD) is the automation of the gamification design process using data mining approaches to apply game design elements tailored to each individual that maximizes their expected contribution to achieve well-defined objectives.

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