Shall we play? – Extending the Visual Analytics Design Space through Gameful Design Concepts

Rita Sevastjanova*
University of Konstanz

Hanna Schäfer†
University of Konstanz

Jürgen Bernard‡
University of British Columbia

Daniel Keim§
University of Konstanz

Mennatallah El-Assady¶
University of Konstanz

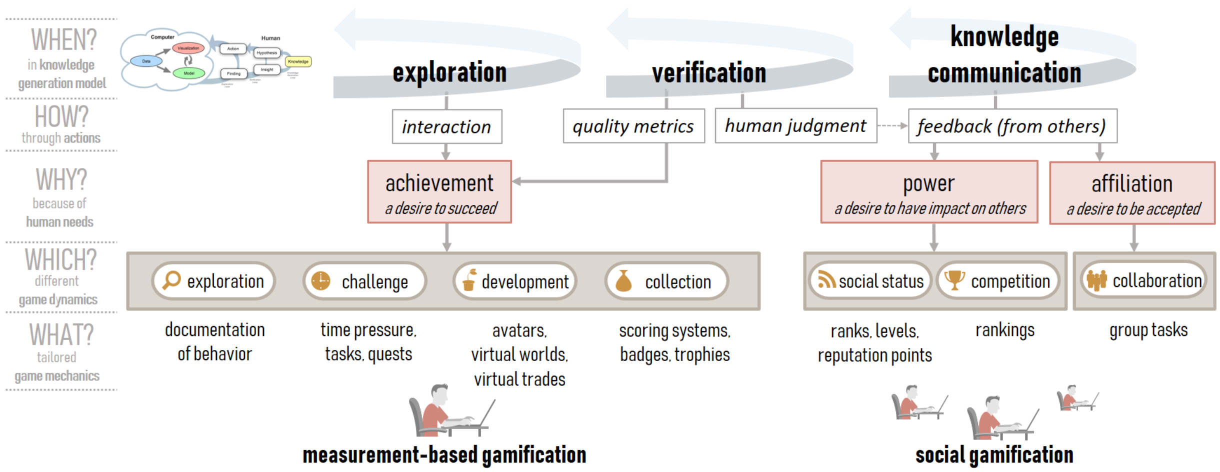


Figure 1: We describe a model for enhancing visual analytics with gameful design concepts through answering five questions: (1) ***When*** does the challenging task occur? – In the three loops of the **knowledge generation model**. (2) ***How*** can we measure what the users do to design an engaging solution? – Through interactions, quality metrics, personal user judgment, and feedback. (3) ***Why*** do people do those challenging tasks? – Human motivation can be characterized by three needs [28]: the need to succeed, to have impact, and to be accepted. (4) ***Which* game dynamics** support these needs? – Different dynamics for different needs. (5) ***What*** are the **game mechanics** suitable for the different dynamics? – Different mechanics for different dynamics.

Abstract

Many interactive machine learning workflows in the context of visual analytics encompass the stages of exploration, verification, and knowledge communication. Within these stages, users perform various types of actions based on different human needs. In this position paper, we postulate expanding this workflow by introducing gameful design elements. These can increase a user's motivation to take actions, to improve a model's quality, or to exchange insights with others. By combining concepts from visual analytics, human psychology, and gamification, we derive a model for augmenting the visual analytics processes with game mechanics. We argue for automatically learning a parametrization of these game mechanics based on a continuous evaluation of the users' actions and analysis results. To demonstrate our proposed conceptual model, we illustrate how three existing visual analytics techniques could benefit from incorporating tailored game dynamics. Lastly, we discuss open challenges and point out potential implications for future research.

Index Terms: Visual Analytics—Gameful Design;

*e-mail: rita.sevastjanova@uni-konstanz.de
†e-mail: hanna.schaefer@uni-konstanz.de
‡e-mail: jubernar@cs.ubc.ca
§e-mail: daniel.keim@uni-konstanz.de
¶e-mail: mennatallah-el-assady@uni-konstanz.de

1 Introduction

Visual Analytics combines the computational power of algorithmic models and the users' domain knowledge to solve complex data analysis tasks. Users play an essential role in this process, being able to interpret visualizations, search for patterns, verify generated machine learning (ML) models, or steer the models to achieve better results. Commonly, mixed-initiative systems enable bringing humans in the analysis loop; there is a joint effort of the user and the computer [16]. The tasks are often complex and time-consuming (e.g., due to the size of the data), and may lead to a loss of motivation and engagement. In a visualization context, user engagement is described as "users' investment in the exploration of a visualization." [4] In recent years, engagement and related concepts like enjoyment and fun have been successfully established in many fields (e.g., crowdsourcing, teaching, healthcare applications). Similarly, design goals in fields of data visualization have expanded from usability goals, such as effectiveness, efficiency, safety, and learnability, to further objectives, including fun, enjoyability, and engagement [39]. Despite that, these concepts are relatively new in visual analytics.

Why is user engagement in visual analytics so important? In order to reach analysis goals (e.g., to find relevant information), the users commonly have to undertake multiple tasks. Many users start their analysis by exploring the data space, creating and steering ML models, and using them to detect elements of interest, which is known as the *exploration loop* in the *knowledge generation model* by Sacha et al. [38]. After having explored the data, users often aim for the validation of extracted information in a *verification loop* by obtaining evidence and (potentially) representing the information schematically [34]. When valid pieces of information are detected, the users generate new knowledge about the data referred to as *knowledge generation loop* [38]. Finally, the data analysis process is often concluded by presenting the found information [5], i.e., by sharing insights. We refer to knowledge generation in combination to sharing the information as *knowledge communication* step.

Due to several reasons, the users may **lose motivation** in different sensemaking steps and in consequence, fail to reach deeper levels of analysis. A primary challenge in the sensemaking process is to deal with the large amount of data. Tasks like exploring the data or searching for interesting data points in a large dataset may seem unproductive and thus lead to a loss of user motivation, but they are critical to iteratively finding meaningful insights in the data [35]. The verification of the patterns and reasoning about data, in contrary, demand a high cognitive load, and are constrained by time pressures, data scales and complexities that can negatively influence the process of generating and evaluating hypothesis [16, 34].

To support motivation, it is important to understand **the concept of motivation** first. According to *McClelland's Theory of Needs* [28], the desire to overcome challenging situations lies in the nature of a human. This theory states that all people regardless where they come from or how old they are, have three needs that influence their behavior: **achievement** (a desire to succeed), **power** (a desire to have an impact on others), and **affiliation** (a desire to be accepted). If these needs are satisfied, people become more motivated. **Enhancing the motivation** is a promising approach to maintain user engagement and that applies to all three visual analytics steps: the users should be motivated to (1) explore the data, continue the extraction of information and generation of ML models; (2) search for valid information or improve the quality of the generated ML models; (3) generate and share new knowledge. Motivational concepts only work when applied at the right time and in the right way. To determine this, we need an automatic analysis of the user/situation that enables the generation of motivational elements.

We postulate that **gameful design** is a means to further strengthen user engagement while fulfilling challenging tasks in visual analysis of data. Gameful design is closely related to **gamification**. According to Deterding, "gameful design and gamification frame the same extension of phenomena through different intensional properties – as the design *strategy* of using game design elements (gamification) or the design *goal* of designing for gamefulness (gameful design)." [11] Gamification uses game elements (e.g., points, levels, badges) in non-game applications having user motivation as its core drive [21]. Gameful design aims at providing freedom of choice [27], personalized experience [31], and long term interaction [25], all relevant for visual analytics applications. Although frequently applied in crowdsourcing and education applications, gameful design is new to the visual analytics community. To the best of our knowledge, no research has been done on exploring the potential of applying gameful design concepts in visual analytics applications.

In this paper, we address this research gap by introducing gameful design elements for visual analytics to strengthen user engagement. Our line of approach is to use established methodologies from either field, bring them together, and show their applicability. We derive the model for augmenting visual analytics processes described by Sacha et al. [38] with game mechanics [3] and motivate the particular alignment of visual analytics steps to game design elements by the *McClelland's Theory of Needs* [28]. Furthermore, we showcase three example use-cases for applying gameful design elements in existing visual analytics applications for improving topic modeling results [13–15]. We show the potential of creating gameful design solutions in an automated manner by learning from user interactions. Building upon these contributions, we discuss potential applications for future research like how to detect the most challenging tasks based on user interactions, or how to adapt the gamified design to a particular user type in an automated way.

2 Background

In this section, we describe the previous work concerning human sensemaking processes in visual analytics, the main concepts of gamification, and its current role in the context of visual analytics.

2.1 The Knowledge Generation Model

Building upon pioneer methodologies in visual analytics [23, 34], Sacha et al. [38] have presented a **knowledge generation model**. They split the visual analytics process into two parts and model the cognitive processes of the human explicitly. In this knowledge generation model [38], the knowledge generation process is described by three loops: (1) the exploration loop, (2) the verification loop, and (3) the knowledge generation loop. In the exploration loop, the analysts interact with the visual analytics system to generate new visualizations or models and explore the data. In the verification loop, the analysts conduct confirmatory analyses in order to reveal findings that confirm or reject hypotheses. The confirmatory analysis may include tasks such as identification, comparison, and summarization of the found data elements [5]. Finally, in the knowledge generation loop, the analysts gain new knowledge about the data. All of these steps are crucial for the analysis. Nevertheless, data overload and complex analysis tasks may limit user engagement [34, 35] and influence the analysis results negatively. We explore the challenges faced during each of these steps and suggest to apply targeted gameful design elements for strengthening user motivation.

2.2 Gamification

In their survey on gamification in theory and action, Seaborn and Fels define gamification as "the intentional use of game elements for a gameful experience of non-game tasks and contexts." [41] The main quality of gamification is its motivational aspect. It prompts the users to stay engaged, e.g., by challenging them to complete given tasks in a limited time-frame or by rewarding them for solving specific assignments. According to Deterding [10], gameful systems have to both directly support end-user activity and facilitate the activity through enjoyment and motivation. According to Ryan and Deci, "to be motivated means to be moved to do something." [36] Motivation can be twofold: it can be (1) driven from within the user because the task is interesting and enjoyable (so-called intrinsic motivation) or (2) derived from an external factor, such as a goal, purpose, or reward (extrinsic motivation) [36].

Most of the applications using gameful design apply game elements, such as points, achievements, leader boards, levels, virtual items, quests/missions, avatars, collections, unlocking, engagement loops, onboarding, competition, cooperation, or feedback [11]. We use the categorization of game elements by Blohm and Leimeister [3] as a reference to show their applicability in the three steps of the knowledge generation model. The authors categorize the game elements according to **motives**, **dynamics**, and **mechanics**. In their framework, mechanics are the *building blocks* of the design such as scoring systems or rewards, and game dynamics describe the *effects* of these mechanics (e.g., a challenge or social status).

2.3 Gamification in Visual Analytics

Although gamification has been successfully applied in different domains, such as teaching [24] (e.g., to increase student motivation to learn), crowdsourcing [29] (e.g., to engage people to label data), or healthcare applications [9] (e.g., to increase motivation to take care of own health), it is relatively unexploited in the context of visual analytics and interactive ML. One of the rare applications of gamification in visual analytics is presented by Ahmed and Mueller [1]. The authors explicitly apply gamification methodology for evaluating visual analytics systems. By supporting entertainment, pleasure, and strengthening the user's feeling of success, they recruit humans for participation in the evaluation of visual analytics systems.

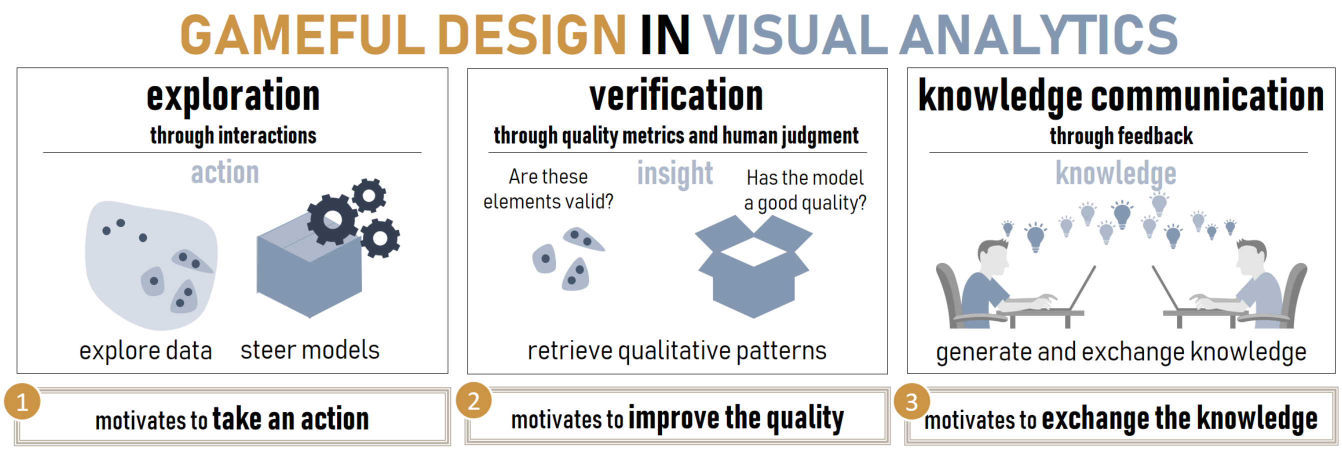


Figure 2: In the three loops of the knowledge generation model by Sacha et al. [38], the gameful design can be used to motivate the users to (1) take an action, (2) improve the quality of insights and generated models, and (3) exchange the insights.

3 Gameful Visual Analytics

In this section, we present the ***GamefulVA*** model for augmenting visual analytics processes with game mechanics. In order to guide other researchers to game mechanics tailored to specific user tasks, our model looks at five layers, as shown in the Fig. 1, each answering a specific question: (1) ***When*** *are users performing a (challenging) task?* (2) ***How*** *are users executing that challenging task?* (3) ***Why*** *are users performing such tasks, i.e., which needs do they have?* (4) ***Which*** *game dynamics can support their needs?* (5) ***What*** *are the game mechanics supporting these dynamics?*

To illustrate the described concepts in each layer, we use the following running-example: *In a classroom setting, students are asked to refine a clustering model for housing offers by interacting with a visual analytics system.* We show how each of the introduced concepts can be applied through this simplified example scenario.

3.1 *When* are users performing a (challenging) task?

Sacha et al. [38] model the human cognitive processes based on three loops, i.e., information exploration, verification, and knowledge generation. To suggest an appropriate gameful design for a specific visual analytics task, we, first, describe the characteristics of tasks executed in each knowledge generation loop (summarized in Fig. 2).

Exploration Loop In the exploration loop, the users interact with the system by performing actions in order to gather findings or generate new ML models. *For instance, in our example, the students would start by exploring the different clusters and visualized data points, i.e., housing offers, to gain an understanding of the clustering model.* According to Perer and Sheiderman, the exploration can be divided into systematic exploration where the search covers the data space and "guarantees that all measures, dimensions and features of a data set are studied" [33], and flexible exploration, i.e. open-ended search. Systematic exploration is rarely applicable on complex problems though; otherwise, their solutions could be automated [33]. The exploration process, which is usually at least partly open-ended, is a crucial first step in the analysis, yet, due to data overload, it can become overwhelming and challenging for the users to find diverse data instances. In situations when the users lose engagement to continue the exploration process, there is a need to **motivate them to take or continue an action**.

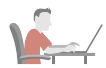
Verification Loop In the verification loop, the users interpret properties of the retrieved *patterns* (e.g., a combination of data points, ML models) in order to apply them to generate or verify hypotheses or to gain new insights about the data. If these patterns are not sound (i.e., the models are not accurate), the users may return to the exploration loop and continue the exploration process or the refinement of a ML model. The verification of the patterns is performed in the context of the problem domain. *In our example, the verification task of the students is to refine the clustering model by detecting housing offers that would belong to another cluster and consequently update the clusters. That could be done by applying quality metrics such as intracluster/intercluster distances.* Frequently, the analysis tasks are complex, and the verification of the findings demands a high cognitive load. The reason is that users process information in their "working memory", which has limited capacity [20]. Complex visualizations and tasks, in general, may impose a high cognitive load and overwhelm the users, resulting in a poor performance. We argue for a design that turns complex and frustrating tasks into engaging activities and **motivates the users to continue the verification process leading to qualitative insights and more accurate models**.

Knowledge Communication Loop Finally, in the knowledge generation loop, the users gain knowledge when they trust the gained insights. Sacha et al. [38] are not explicitly describing what happens after the knowledge is obtained. The next step is important, as then the knowledge can be applied in practice, *communicated* and evaluated by other domain experts, as well as integrated into visual analytics systems to support the generation of new knowledge. Federico et al. in their conceptual model of knowledge-assisted visual analytics emphasize the role of explicit knowledge in visual analytics systems and write that it is an "important asset that can be leveraged by both human and computer to improve the analytic process." [17] The goals of knowledge-assisted visualizations are, among others, **sharing domain knowledge** among different users, and **performing cooperative decision making** [45]. Thomas and Cook [45] write that some visual analytics tasks are so complex that "they cannot be addressed by individuals working in isolation." [45] In cooperative systems, not only the *collaborative* dialogue (in which team members share responsibilities) but also *cooperative-competitive* dialogue (team members work toward the same goals but pose competitive explanations) is important [45]. The competitive aspects are well known in the context of gameful concepts as one of the human needs. However, they are rarely applied in the context of visual analytics. We extend the knowledge generation model by going beyond the knowledge of one person and refer to it as *knowledge communication*. This step includes not only sharing the knowledge but also gaining feedback from peers. *In the classroom setting, students could collaborate with their peers, share and combine their findings, and give feedback to reach the best possible quality of the clustering model.* The knowledge communication introduces several challenges (listed in Table 1), such as the need to find a common language, or to trust in own results. We believe that appropriate design can **motivate the users to participate in the knowledge communication, enabling a more effective problem solving**.

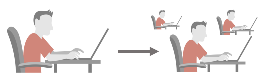
3.2 *How* are users performing the challenging task?

To create motivating design elements automatically, we need to *translate* the actions performed by the users in implementable (realizable) building blocks. In the three analysis loops, the users perform different actions, as shown in the Fig. 2. In the exploration loop, they interact with the system; in the verification loop – they validate findings through quality metrics or their personal judgment; in the knowledge communication loop, they share these findings with other experts, i.e., by exchanging feedback.

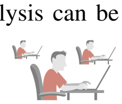
Interactions In the exploration loop, the users perform actions, i.e., interact with the system in order to gain findings and reach their analysis goal. The system has to **measure user interactions** in order to integrate this information into new motivating designs and activities. These measurements can be the performance of exploration, i.e., the pace or uniqueness of the exploration, the number of explored unique data attribute combinations [2], observed data elements, model steering iterations, etc. *In the classroom setting, the system could count and visualize the number of houses that have been explored by a student.*



Quality Metrics and Human Judgment Frequently, to assess quantitative evidence about the quality of gathered findings, the system automatically **measures the properties of insights through quality metrics** or statistical tests. *For instance, when improving the clustering results, the system could continuously evaluate the cluster quality through quality metrics, i.e., intracluster variance*. Often, though, the validation of the found patterns is based on **personal user judgment** according to their previous knowledge about the task and domain. The personal user judgment is hard to be measured and **requires social feedback** for realization in a motivating design.



Feedback In situations when no statistical analysis can be applied to evaluate the performance of the patterns, or the verification concerns higher-level hypotheses, a *wisdom-of-the-crowd* can be helpful. In these situations, the users can ask for **qualitative feedback** from colleagues, domain experts, or collaborators. Furthermore, people can collaborate and combine their insights to present knowledge from a broader perspective. *When refining clustering results, the students could ask their peers for feedback to improve the model's performance.*



3.3 *Why* are users executing challenging tasks, i.e., which needs do they have?

Although some visual analytics tasks are very complex and challenging, the users have the intrinsic wish to attain them. Domain experts use visual analytics system to **support their primary tasks**, for understanding specific patterns hidden in the data. The explanation of why people have the desire to overcome challenging situations lies in the nature of a human. According to McClelland [28], every human has three needs: (1) the need for **achievement**, (2) the need for **power**, and (3) the need for **affiliation**.

Achievement According to the *McClelland's Three Needs Theory*, people want to succeed when they are performing a task. This desire is independent of their gender, culture, or age. In visual analytics, the users aim to achieve the targeted analysis goal. In particular, they aim to accomplish all smaller sub-tasks which are part of the analysis: first, to find relevant data points and patterns or generate a ML model; second, to create qualitative models and find valid patterns. *While refining the clustering model, the students could have multiple goals in mind. First, they might want to succeed in finding interesting houses with unique attribute values in the exploration loop. Second, in the verification loop, they might strive to improve the overall performance of the model or the quality of one specific cluster, by removing inappropriate houses from it. By accomplishing each of these goals, they would gain a feeling of success.* According to the motivation theory, the more achievements people make, the higher the level of motivation they have and, thus, a higher level of performance [28]. Therefore, it is important to integrate and visually display important user achievements in the system for a stronger user motivation.

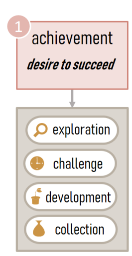
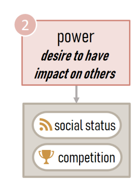


Table 1: Due to several reasons, such as the complexity of analysis task, the overload of data, or missing common methods to communicate knowledge in the context of visual analytics, each of the knowledge generation loops can introduce challenges for the users.

TASKS	CHALLENGES
EXPLORATION	
Explore data and model space.	Too large data space. No clear starting or end point. Covers only a subspace of the data. Time-consuming to cover the whole space. The found information can be forgotten. Underestimates the importance of this task.
Build, steer, and apply a model.	The impact of the work is not visible. Generation of a *good* model takes time. A monotonous task. Requires a high cognitive load. Concern of being unable to apply the model. A huge parameter space.
VERIFICATION	
Verify found patterns and created models.	Unawareness of the novelty of the findings. Missing important differences. Generation of a *good* model can be difficult. Requires a high cognitive load.
KNOWLEDGE COMMUNICATION	
Generate and share knowledge.	Find common language. Expose own results. Trust in own results. Transparent interaction.

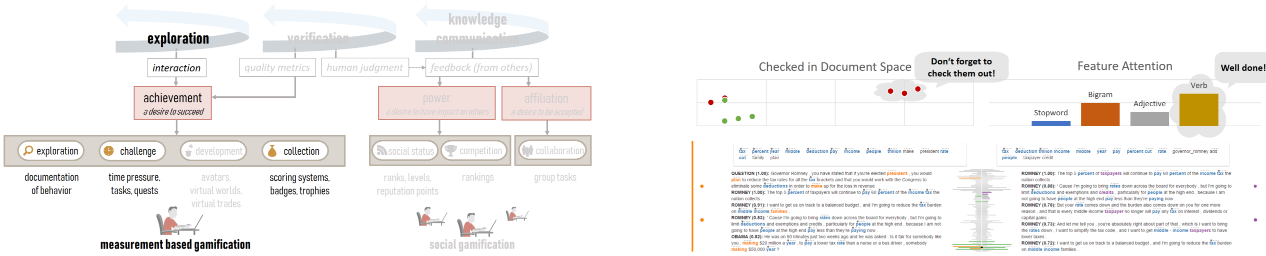
Power The need for power implies that every human wants to have an impact on others. People want to raise their self-esteem and reputation; they want to have control over others, and be better than others. For instance, in visual analytics, the users aim at creating ML models with higher accuracy than the existing models. *In the classroom setting, the students would want to improve the performance of the clustering model in order to polish their social status or compete with other students.*



Affiliation The need for affiliation signifies that everyone wants to be liked and accepted, and belong to a group. People want to have social relationships to others. Also, in visual analytics, collaborative systems are used to enable the users to combine their knowledge and ideas for better analysis results. *For instance, the students could separate the task – every student could work on improving one specific cluster; then, the findings could be shared with the rest of the group and incorporated into one system for developing a qualitative model.*

3.4 *Which* game dynamics support human needs and *what* are the game mechanics for each dynamic?

Every human is motivated by the three needs with varying priorities, i.e., achievement, power, and affiliation. We introduce gameful concepts as an effective approach to create a supportive design for these needs in visual analytics applications. The gameful design supports



(a) In the exploration loop, users can be motivated through **exploration**, **challenge**, and **collection** dynamics, raising their *sense of achievement*.

(b) Augmenting the visual interface through the **documentation of behavior** mechanic. The system can give feedback on explored data regions and the covered data characteristics.

Figure 3: Suggested extension for the technique of *progressive learning of topic modeling parameters* [14]. It can be enriched by measurement-based gamification to motivate the users to, first, carefully explore the document space, before starting to engage with the iterative refinement.

the three needs by tailored game dynamics and mechanics. There exist a large variety of game elements in the literature; we use the categorization of game elements by Blohm and Leimeister [3] for a reference. According to Deterding [10], gamification should combine dynamics in a meaningful way creating an engaging narrative. Each game dynamic can be implemented through different game mechanics, i.e., gameful design building blocks [3]. These mechanics describe concrete approaches for realizing the goals outlined by the game dynamics (e.g., rewarding users with *badges* for reaching a new level in a *challenge* dynamic).

We separate the dynamics into **measurement-based gamification** which implementation requires quantitative measurements and **social gamification**, which enables communication and exchange.

Measurement-based Gamification The feeling of success or achievement can be gained by applying game dynamics, such as **exploration**, **challenge**, **development**, and **collection**. These dynamics can be implemented through measurements estimated in the exploration or verification loop. *For instance, the students who have found a distinct amount of interesting houses which do not belong to a specific cluster would have a sense of success if they knew how many points are likely to be clustered wrong; thus, the gamified design could use quality metrics as a point of reference and reward the users for improving the model's performance*.

exploration

Exploration supports user intellectual curiosity, and it can be designed through **documentation of behavior** that "visualizes progress, facilitates the derivation of achievable personal goals and offers immediate feedback." [22] *For instance, the system could visualize the exploration path to motivate the students to search in not yet explored data regions.*

challenge

Challenge is a situation in which the outcome requires an effort to accomplish [42]. It provides cognitive stimulation, and can be designed through **time pressure**, **tasks**, or **quests**. *For instance, the system could challenge the students to improve the quality of a specific cluster, letting them to observe only a limited number of houses in a limited time.*

development

Development shows the evolution of user skills while solving a task. According to the self-determination theory, everyone wants to build his competence and improve his skills [37]. Development can be designed by **avatars**, **virtual worlds**, or **virtual trades**. *For instance, the system could motivate the students by showing the changes in the cluster quality and visually acknowledge significant quality improvements.*

collection

Collection enables the user to gather rewards for performed actions. People like to collect things for their awareness of ownership and possession [8]. Collection can be designed through **scoring systems**, **badges**, or **trophies**. *For instance, the students could create a collection of houses that they had placed in a correct cluster.*

Social Gamification **Social status**, **competition**, and **collaboration** are among those game dynamics, which are tailored to support power and affiliation needs. These dynamics can be implemented by integrating feedback from colleagues or collaborators with respect to the gathered findings or generated knowledge, e.g., by visualizing the assessed performance of the user or by motivating the users to perform better through competition. *The design of the tool for clustering refinement could use student feedback as a quality criterion to socially acknowledge student' attainments.*

social status

Social Status enables sharing user achievements to others with the purpose of social recognition. According to Hamari and Koivisto, "receiving recognition creates willingness to recognize others reciprocally within a service." [19] It can be designed through **ranks**, **levels**, or **reputation points**. *For instance, the system could acknowledge those students who found the clusters with the highest error rate.*

competition

Competition enables multiple users to compete with each other; this dynamic is motivating because "it provides a challenge at an appropriate difficulty level." [26] Competition can be designed through **rankings**. *For example, the system could enable the students to compete with each other for finding the cluster with the highest error rate first.*

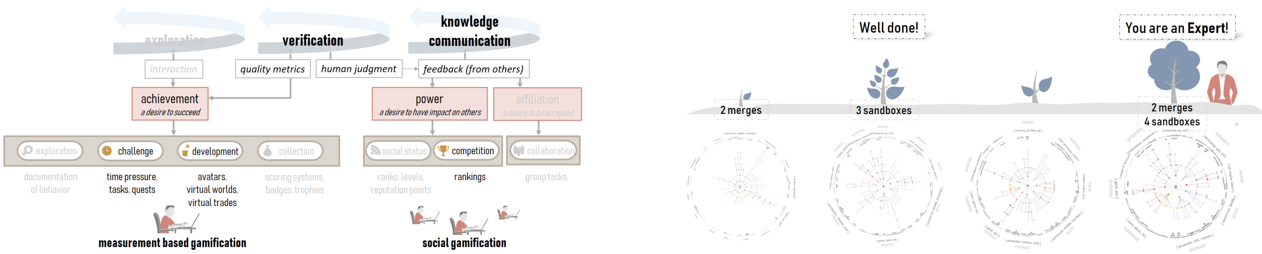
collaboration

Collaboration is known as the efforts of multiple individuals towards one desired outcome [6], and it can be designed through **group tasks**. Besides direct collaboration, **collaborative interactions** can also implement the collaboration dynamic. *For instance, the students could analyze different clusters and combine their insights in a collaborative setting.*

4 Use Cases: Gameful Topic Model Refinement

To demonstrate our conceptual model, we describe how gameful design can be integrated into existing visual analytics systems. To show the variety of possible gamification applications, we apply the model on three systems from one domain, here: *Topic Modeling* (TM). TM algorithms belong to the class of unsupervised ML and are frequently used to analyze thematic concepts in text data. However, it is difficult to interpret how these algorithms work, and it is challenging to adapt them to given data.

In the context of the lingvis.io framework [12], three visual analytics techniques for refining TM have been developed, each targeting a different user group. All of these approaches target the tasks of understanding, diagnosis, and refinement [44] of the ML model at hand, i.e., TM. We use these three comparable techniques as prototypical use cases for explainable and interactive ML, discussing how such techniques would benefit from applying gameful concepts within their proposed analytical processes.



(a) In the **verification loop**, the users can be motivated through the **challenge** and **development** dynamics; in the **knowledge communication loop**, through **competition**.

(b) The **development** of the users can be shown by a timeline recognizing their activity and interactions toward improving the model's performance.

Figure 4: The *SpecEx* technique [15] can benefit from challenging users to continuously improve the model's quality, and communicate their performance to others as a competitive feedback. Using such gamification dynamics, we can target the users' *sense of achievement and power*.

4.1 TM Refinement through Parameter Optimization

Many domain experts, e.g., linguists or political scientists, use TM algorithms in their research. Nevertheless, often, experts have difficulties in interpreting the created results and adapting the models to a given data. The *progressive learning technique* [14] helps analysts (experts and non-experts, alike) to intuitively adjust the models without the need to understand the models' inner working mechanisms. In this approach, reinforcement learning is used for integrating user feedback and adapting TM keyword weights. This process, although simple and intuitive, requires the users to explore the data first in order to get an overview of the feature and topic distributions. When using large text corpora, this exploration can be time-consuming, reducing the users' engagement.

According to the *GamefulVA*, this type of challenging task is part of the **exploration loop**. We thus want to support the *sense of achievement* the users want to gain from conducting their exploration through extending the system by several measurement-based gamification elements, as shown in Fig. 3. For our use case, we sketched one possible integration of an *exploration* dynamic and a *collection* dynamic. The **exploration** dynamic could be provided by visually documenting the exploration of the text corpora. The **collection** dynamic could be used for motivating the users to explore documents with dissimilar feature distributions, e.g., by collecting feature attention points. In addition to this visual feedback, the system could **challenge** the user to find *x* documents with a predefined feature distribution in a predefined time, ensuring that the user has understood where and how to find documents with specific characteristics. Altogether, these three or other similar game mechanics could motivate users of a progressive learning system to continue exploring the document space and thus to keep improving the model's quality in the continuous reinforcement learning loop.

4.2 TM Refinement through Speculative Execution

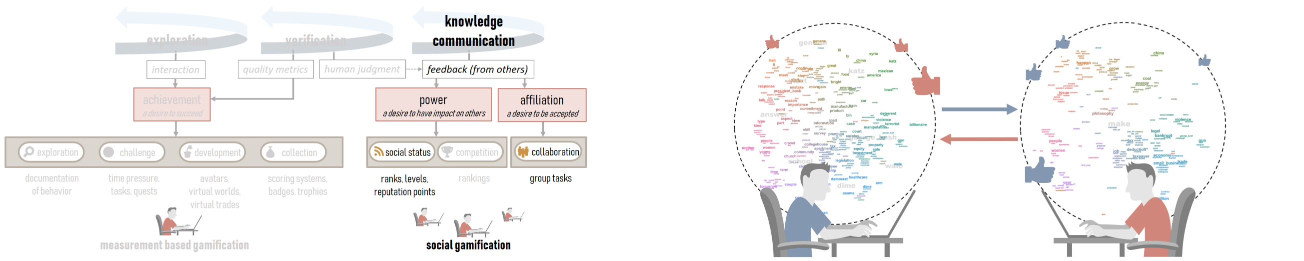
SpecEx [15] visually explains the topic model generation process (using a topic-tree). It enables the monitoring of model quality changes and supports users to optimize the model manually by integrating their domain knowledge throughout the model generation steps. The system provides a concept of speculative execution [43] "for creating user-steerable preview mechanisms" [15], which points the users to topics that require a quality improvement and requests users' feedback every time the quality of the model decreases. In situations when the performance decreases, users can explore the suggested optimizations (presented in, so-called, sandboxes) and decide to accept or reject them. Optimization of large text corpora can be very time-consuming. It is especially challenging for users to continuously invest a high cognitive effort into studying the optimization alternatives instead of simply choosing the best rated strategy.

According to the conceptual model, this type of challenging task is both part of the **verification loop** and the **knowledge communication loop**, as shown in Fig. 4. In the **verification loop**, we propose to support the *sense of achievement*, e.g., through rewarding users performing multiple model optimizations. In the **knowledge communication loop**, we want to increase the *sense of power*, e.g., by letting the *human judgment* compete with the best-rated strategies, or with other users. For our use case, we sketched one possible integration of how a **development** dynamic could show the progress of the model's performance through different quality metrics updated throughout the model generation steps and visually highlight the achieved quality improvement (shown in the Fig. 4b). In contrast to the progressive learning system, a **challenge** dynamic could be applied in the **verification loop** by demanding, e.g., steady improvement of the model's performance. This challenge would require the user to explore the different optimization strategies carefully and to avoid making prompt decisions. Finally, the system could be extended by a **competition** dynamic which allows domain experts working with topic modeling algorithms to compare the quality of each other's or the machine's created topic-trees.

4.3 TM Refinement through Semantic Interactions

The *Semantic Concept Spaces* technique [13] is designed to enable users to externalize their domain knowledge through refining concept relations using semantic interactions. These concept relations are detached from the TM to enable a model-agnostic refinement. Based on the changes made in the so-called, concept spaces (the semantic interface), the model learns a refined representation of topics and reacts by readjusting the topic view. For a targeted refinement, it *guides* the users through the space to the uncertain areas and suggests actions for refining the model. Hence, by readjusting the concept space, users externalize their domain understanding, producing a visual representation of their mental model that can be used to teach a TM. In addition, such concept spaces can be used across corpora (to learn a semantic representation of a particular domain, e.g., news data). Thus, sharing and collaboratively refining concepts is an essential task, as every user has a subjective opinion about the correctness of semantic concept relations. This needs to be supported by methods for iteratively comparing and improving concepts.

According to our conceptual model, this type of challenging task is part of the **knowledge communication loop**. We thus want to support the *sense of power* and *affiliation* that users want to gain from exchanging their ideas with other colleagues by extending the system with several *social* gamification elements, as shown in Fig. 5. For our use case, we sketched a possible integration of both **social status** dynamics and **collaboration** dynamics to compare the users' semantic concepts. The system could enable users to give feedback on TM results created by their colleagues. Positive feedback could acknowledge and thus motivate the users to continue their work. Such feedback could also inspire other users who work on similar tasks; they could adapt their models based on new insights. The interface could also support collaborative settings, where multiple users at the same time work on refining the same topic model.



(a) In the **knowledge communication loop**, by introducing *social gamification*, users can be motivated through **social status** and **collaboration** dynamics.

(b) To increase engagement, in a **collaborative** interface, the users can give feedback to the models created by their colleagues, as well as receive feedback for their own models.

Figure 5: Suggested enhancement for the *Semantic Concept Spaces* technique [13] to support collaborative domain knowledge externalization by communicating the concept spaces of different users, enabling them give and receive feedback, exchanging their *mental model depictions*.

Through the interface, the users could discuss different alternative representations of the concept space and potentially come up with a more robust (less subjective) topic model. The combination of social status and collaboration elements is especially fruitful since the collaboration can benefit from mutual trust within a group, once the social status of every member has been established.

5 Discussion of Research Implications

In this section, we discuss research and application opportunities created by the introduction of the *GamefulVA* model. One crucial requirement for operationalizing the *GamefulVA* model is the detection of user types and contexts from their interactions. Furthermore, we give an overview of the inherent challenges and limitations that gameful design is facing and how they might influence *GamefulVA*.

5.1 Opportunities and Applications

The *GamefulVA* model spans a new design space for visual analytics systems. This design space creates many research opportunities regarding the operationalization of *GamefulVA*. Especially the application of machine learning to derive user characteristics and contextual challenges from interactions can boost the automatic generation of meaningful and effective gameful design concepts.

Automatic detection of challenging situations - To provide a suitable gameful solution, the system has to identify when users are facing challenges. The system could learn from user interactions, whether they are struggling, and which gamified design is needed to overcome the challenging situation. Detection of challenging situations is conceivable in all three core phases of the analysis process. Using the exploration pace of users as an example, motivation decrease may be detected automatically. A similar scenario may occur when all low-hanging fruits have been explored already. The steadiness of model quality changes might indicate whether the user struggles with the verification of his ideas. One could go even one step further and apply models trained on data gathered by physiological or physical sensors to reveal the level of user frustration [32].

Flexibility of gameful design pipeline - Gamified applications often integrate game dynamics into a complete and engaging narrative. The combination of gameful elements must be meaningful and situation-dependent [10]. Two aspects where flexibility in applying gameful design in visual analytics can be particularly useful are (1) considering the dynamic pipeline and (2) the adjustment of dynamic constraints. It would be interesting to explore, how to continuously and automatically update a pipeline of game dynamics to provide an appropriate dynamic for the user needs in a particular situation. Furthermore, the constraints of a dynamic (e.g., the complexity of a challenge, a threshold for a time pressure dynamic) could be updated by taking the previous activity of the user into account. For instance, the system could learn a proper time-threshold for the time pressure dynamic through different exploration-metrics [18], i.e., the number of data-points the user interacted with in the first x minutes after being introduced with the system.

Assessing the effects of game elements - With the *GamefulVA* model, it is now possible to integrate and assess the effects of different game dynamics for different visual analytics processes. Promising research directions are the evaluation of game dynamics on specific tasks conducted by a predefined user-type, to understand its impact on users' motivation or their performance.

Personalization of gameful design - The extension of the visual analytics design space through gameful design concepts creates room for new personalization approaches. Such personalization is vital for user types with different levels of acceptance for gameful elements. Automatic tailoring of the invasiveness of gameful design concepts could range from the individualization of data- and control flows to the visual representation of data, as well as the view transformation. Research into this interesting topic can be fostered in different ways, including methodological aspects (like evaluations, discussions, and reflections), as well as technique-driven approaches focusing on measuring gamification effects and deriving user preferences.

Gamification as an extension for user guidance - User guidance has gained importance in visual analytics systems. This is especially necessary due to the data overload and the complexity of the used models. Guidance can be categorized into prescribing, directing, and orienting guidance [7, 40]. While guidance wants to ease the interaction with a system to increase engagement, gamification tries to create additional challenges in the interaction to increase motivation. Gamification could thus work as an alternative to directing and orienting guidance mechanics.

5.2 Challenges and Limitations

While *GamefulVA* offers a lot of opportunities for research regarding an improved VA experience, the gameful design itself is an active area of research with several unsolved challenges and limitations.

Ambiguitiy of gamification methodology - In the gamification community, different approaches exist how to categorize game elements (cf. Section 2.2). Related to that, parts of the terminology may vary across different categorizations. While the commonly used definition of **mechanics** as design building blocks by Blohm and Leimeister [3] was useful for this approach, other categorizations may be interesting to be linked to the visual analytics design space as well. Example alternatives include the meaning of mechanics proposed by Werbach and Hunter [46].

Evaluation of gameful designs - Another challenge will be to design best practices for evaluating and measuring the effects of game elements. Evaluation of game elements is a viable sub-topic in gamification research. However, the scope of measured effects of game elements today (points, badges, levels, or leaderboards) is still limited in current systems that apply gamification, e.g., in teaching [30]. An interesting line of future work is to elaborate on how visual analytics, in particular, can foster such assessments.

Gamification can be considered too playful - Some people still associate gamification with its supposed lack of seriousness and a loss of quality in analytic systems. This shows the importance of an open discussion, clarification, and empirical evaluation of the benefits gamification brings to visual analytics.

Gamification can be considered harmful - Inappropriate application of gamification elements might encourage users to take unnecessary actions or refine a model in the wrong way (e.g., cause overfitting). Just as the concepts of guidance and explanations can lead to misguiding the users, potential consequences of gamification elements need to be evaluated carefully. Control over the process and the assessment of user effects may help to identify harmful situations and to counter-balance negative effects.

6 Conclusion

This paper proposes an extension of the visual analytics design space through gameful design concepts. It shows how gameful design can foster three types of motivation during (challenging) analysis tasks in each of the loops of the knowledge generation model [38]. It further discusses how the type of quality assessment in each loop influences the choice between measurement-based and social game dynamics. Finally, three different use cases demonstrate how the *GamefulVA* model can be used to select and design fitting game dynamics. We postulate that this model may help researchers to identify game elements for a challenging visual analytics task in their system. Finally, we discuss how *GamefulVA* can be evaluated and extended with the help of machine learning and which challenges the application of gameful design might entail.

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References

[1] N. Ahmed and K. Mueller. Gamification as a Paradigm for the Evaluation of Visual Analytics Systems. In *Proc. of the Fifth Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization*, pp. 78–86. ACM, 2014.

[2] L. Battle and J. Heer. Characterizing Exploratory Visual Analysis: A Literature Review and Evaluation of Analytic Provenance in Tableau. In *Computer Graphics Forum*, vol. 38, pp. 145–159. Wiley Online Library, 2019.

[3] I. Blohm and J. Leimeister. Gamification – Design of IT-Based Enhancing Services for Motivational Support and Behavioral Change. *Business and Information Systems Engineering*, 5:275–278, 2013.

[4] J. Boy, F. Detienne, and J.-D. Fekete. Can Initial Narrative Visualization Techniques and Storytelling help Engage Online-Users with Exploratory Information Visualizations. *Proc. of the CHI, Seoul, Korea*, pp. 18–23, 2015.

[5] M. Brehmer and T. Munzner. A Multi-Level Typology of Abstract Visualization Tasks. *IEEE Trans. on Visualization and Computer Graphics*, 19(12):2376–2385, 2013.

[6] R. Briggs, G. Kolfschoten, V. Gert-Jan, and D. Douglas. Defining Key Concepts for Collaboration Engineering. *AMCIS 2006 Proc.*, p. 17, 2006.

[7] D. Ceneda, T. Gschwandtner, T. May, S. Miksch, H.-J. Schulz, M. Streit, and C. Tominski. Characterizing Guidance in Visual Analytics. *IEEE Trans. on Visualization and Computer Graphics*, 23(1):111–120, 2016.

[8] Y.-K. Chou. *Actionable Gamification: Beyond Points, Badges, and Leaderboards*. Createspace Independent Publishing Platform, 2015.

[9] R. De Croon, D. Wildemeersch, J. Wille, K. Verbert, and V. V. Abeele. Gamification and Serious Games in a Healthcare Informatics Context. In *2018 IEEE Int. Conf. on Healthcare Informatics (ICHI)*, pp. 53–63. IEEE, 2018.

[10] S. Deterding. The Lens of Intrinsic Skill Atoms: A Method for Gameful Design. *Human–Computer Interaction*, 30(3-4):294–335, 2015.

[11] S. Deterding, D. Dixon, R. Khaled, and L. Nacke. From Game Design Elements to Gamefulness: Defining "Gamification". In *Proc. of the 15th Int. Academic MindTrek Conf.: Envisioning Future Media Environments*, pp. 9–15. ACM, 2011.

[12] M. El-Assady, W. Jentner, F. Sperrle, R. Sevastjanova, A. Hautli-Janisz, M. Butt, and D. A. Keim. lingvis.io - A Linguistic Visual Analytics Framework. *Association for Computational Linguistics, ACL System Demonstrations*, 2019.

[13] M. El-Assady, R. Kehlbeck, C. Collins, D. Keim, and O. Deussen. Semantic Concept Spaces: Guided Topic Model Refinement using Word-Embedding Projections. *IEEE Trans. on Visualization and Computer Graphics*, 2019.

[14] M. El-Assady, R. Sevastjanova, F. Sperrle, D. Keim, and C. Collins. Progressive Learning of Topic Modeling Parameters: A Visual Analytics Framework. *IEEE Trans. on Visualization and Computer Graphics*, 24(1):382–391, 2017.

[15] M. El-Assady, F. Sperrle, O. Deussen, D. Keim, and C. Collins. Visual Analytics for Topic Model Optimization based on User-Steerable Speculative Execution. *IEEE Trans. on Visualization and Computer Graphics*, 25(1):374–384, 2018.

[16] A. Endert, W. Ribarsky, C. Turkay, B. W. Wong, I. Nabney, I. D. Blanco, and F. Rossi. The State of the Art in Integrating Machine Learning into Visual Analytics. In *Computer Graphics Forum*, vol. 36, pp. 458–486. Wiley Online Library, 2017.

[17] P. Federico, M. Wagner, A. Rind, A. Amor-Amorós, S. Miksch, and W. Aigner. The Role of Explicit Knowledge: A Conceptual Model of Knowledge-Assisted Visual Analytics. In *2017 IEEE Conf. on Visual Analytics Science and Technology (VAST)*, pp. 92–103. IEEE, 2017.

[18] M. Feng, E. Peck, and L. Harrison. Patterns and Pace: Quantifying Diverse Exploration Behavior with Visualizations on the Web. *IEEE transactions on visualization and computer graphics*, 25(1):501–511, 2018.

[19] J. Hamari and J. Koivisto. Social Motivations to Use Gamification: An Empirical Study of Gamifying Exercise. In *ECIS*, vol. 105, 2013.

[20] W. Huang, P. Eades, and S.-H. Hong. Measuring Effectiveness of Graph Visualizations: A Cognitive Load Perspective. *Information Visualization*, 8(3):139–152, 2009.

[21] K. M. Kapp. *The Gamification of Learning and Instruction: Game-based Methods and Strategies for Training and Education*. Pfeiffer & Company, 1st ed., 2012.

[22] K. Karimi and J. Nickpayam. Gamification from the Viewpoint of Motivational Theory. *Emerging Science Journal*, 1(1):34–42, 2017.

[23] D. Keim, J. Kohlhammer, G. Ellis, and F. Mansmann, eds. *Mastering the Information Age Solving Problems with Visual Analytics*. Goslar : Eurographics Association, 2010.

[24] S. Kiesler, R. E. Kraut, K. R. Koedinger, V. Aleven, and B. M. Mclaren. Gamification in Education: What, How, Why Bother? *Academic exchange quarterly*, 15(2):1–5, 2011.

[25] J. Koivisto and J. Hamari. The Rise of Motivational Information Systems: A Review of Gamification Research. *International Journal of Information Management*, 45:191–210, 2019.

[26] T. W. Malone. Toward a Theory of Intrinsically Motivating Instruction. *Cognitive science*, 5(4):333–369, 1981.

[27] C. Marache-Francisco and E. Brangier. Perception of Gamification: Between Graphical Design and Persuasive Design. In *Int. Conf. of Design, User Experience, and Usability*, pp. 558–567. Springer, 2013.

[28] D. C. McClelland. *Human motivation*. CUP Archive, 1987.

[29] B. Morschheuser, J. Hamari, and J. Koivisto. Gamification in Crowdsourcing: A Review. In *2016 49th Hawaii Int. Conf. on System Sciences (HICSS)*, pp. 4375–4384. IEEE, 2016.

[30] L. E. Nacke and C. S. Deterding. The maturing of gamification research. *Computers in Human Behaviour*, pp. 450–454, 2017.

[31] S. Nicholson. A User-Centered Theoretical Framework for Meaningful Gamification. In *Proc. of Games+Learning+Society 8.0*, pp. 223–229, 2012.

[32] P. Panwar, A. Bradley, and C. Collins. Providing Contextual Assistance in Response to Frustration in Visual Analytics Tasks. In *Workshop for Machine Learning from User Interaction for Visualization and Analytics at IEEE VIS*, 2018.

[33] A. Perer and B. Shneiderman. Systematic Yet Flexible Discovery:

Guiding Domain Experts through Exploratory Data Analysis. In *Proc. of the 13th Int. Conf. on Intelligent User Interfaces*, pp. 109–118. ACM, 2008.

[34] P. Pirolli and S. Card. The Sensemaking Process and Leverage Points for Analyst Technology as Identified Through Cognitive Task Analysis. In *Proc. of Int. Conf. on Intelligence Analysis*, vol. 5, pp. 2–4. McLean, VA, USA, 2005.

[35] L. Ryan. *The Visual Imperative: Creating a Visual Culture of Data Discovery*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1st ed., 2016.

[36] R. M. Ryan and E. L. Deci. Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, 25(1):54–67, 2000.

[37] R. M. Ryan and E. L. Deci. Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American psychologist*, 55(1):68, 2000.

[38] D. Sacha, A. Stoffel, F. Stoffel, B. C. Kwon, G. Ellis, and D. A. Keim. Knowledge Generation Model for Visual Analytics. *IEEE Trans. on Visualization and Computer Graphics*, 20(12):1604–1613, 2014.

[39] B. Saket, A. Endert, and J. Stasko. Beyond Usability and Performance: A Review of User Experience-focused Evaluations in Visualization. In *Proc. of the Sixth Workshop on Beyond Time and Errors on Novel Evaluation Methods for Visualization*, pp. 133–142. ACM, 2016.

[40] H.-J. Schulz, M. Streit, T. May, and C. Tominski. Towards a Characterization of Guidance in Visualization. In *Poster at IEEE Conf. on Information Visualization (InfoVis)*, 2013.

[41] K. Seaborn and D. I. Fels. Gamification in theory and action: A survey. *Int. Journal of human-computer studies*, 74:14–31, 2015.

[42] M. Sicart. Defining Game Mechanics. *Game Studies*, 8(2):n, 2008.

[43] F. Sperrle, J. Bernard, M. Sedlmair, D. A. Keim, and M. El-Assady. Speculative Execution for Guided Visual Analytics. In *Workshop for Machine Learning from User Interaction for Visualization and Analytics at IEEE VIS*, 2018.

[44] T. Spinner, U. Schlegel, H. Schäfer, and M. El-Assady. explAIner: A Visual Analytics Framework for Interactive and Explainable Machine Learning. *IEEE Trans. on Visualization and Computer Graphics*, 2019.

[45] J. J. Thomas. *Illuminating the Path: The Research and Development Agenda for Visual Analytics*. IEEE Computer Society, 2005.

[46] K. Werbach and D. Hunter. *The Gamification Toolkit: Dynamics, Mechanics, and Components for the Win*. Wharton Digital Press, 2015.