Acta Psychologica 228 (2022) 103657

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Gamification for behavior change: A scientometric review

Simone Bassanelli [a,b,*], Nicola Vasta [a], Antonio Bucchiarone [b], Annapaola Marconi [b]

[a] University of Trento, Italy
[b] Fondazione Bruno kessler, Italy

A R T I C L E I N F O

Keywords:
Gamification
Behavior change
Positive behavior
Scientometrics

A B S T R A C T

Gamification, which refers to the use of game design elements in non-game contexts, provides similar experiences and motivations as games do; this makes gamification a useful approach to promote positive behaviors. As a useful tool for keeping users motivated, engaged and active, there is a wide interest in adopting gamification solutions for supporting and promoting positive behaviors and behavior change (e.g. quit smoking, ecological behaviors, food choices, civic engagement, mental healthcare, sustainability, etc.).

In this study, we use the CiteSpace software to examine 984 publications and their 46,609 unique references on gamification applied for behavior change. The corpus of studies was downloaded from the Scopus database and refers to studies published between 2011 and the beginning of 2022. Several methods were used to analyze these data: (1) document co-citation analysis (DCA) was performed to identify the pivotal researches and the research areas; (2) author cocitation analysis (ACA) was performed to identify the main authors; (3) and keyword analysis was performed to detect the most influential keywords and their change over time.

The results of the analysis provide an overview of the influential documents, authors and keywords that have given shape to the literature of the field, and how it has evolved, showing an initial interest in motivational and persuasion techniques, and in the gamification design, and subsequently in the development of more rigorous methodologies for both design and use.

As the first scientometric review of gamification applied to behavior change, this study will be of interest to junior and senior researchers, graduate students, and professors seeking to identify research trends, topics, major publications, and influential scholars.

1. Introduction

The impact of video games has been studied in parallel with the development of the game industry (Dale et al., 2020). Since the early '70s, a growing body of research has been investigating video games' effects on brain functions and behaviors and how they can affect user's motivation and engagement (Reid, 2012). With the development of serious games, researchers started using video games features in non-playful contexts, in order to increase the motivation to overcome challenges and achieve success, and task engagement of users (Alsawaier, 2018; Djaouti et al., 2011; Ryan et al., 2006).

The term gamification, introduced in the early 2000s (Marczewski, 2013), provides a complementary perspective to serious games. This approach uses game elements to enhance non entertainment applications to foster behavioral change, engagement, motivation, and soliciting participation in activities (Dicheva et al., 2019; D. Johnson et al., 2016; Paiva et al., 2020; Ryan et al., 2006). Its further dissemination began in 2011, after the publication of several documents (Deterding, Dixon, Khaled, & Nacke, 2011; Deterding, Sicart, Nacke, O'Hara, & Dixon, 2011; Huotari & Hamari, 2012; Zichermann & Cunningham, 2011), gaining popularity and rapidly spreading in a wide range of domains that benefit from the increased engagement of their target users (Koivisto & Hamari, 2019) such as health and environmental awareness (D. Johnson et al., 2016; Marconi et al., 2018; Rajani et al., 2021; Vieira et al., 2012), e-banking (Rodrigues et al., 2016), software engineering (Pedreira et al., 2015), education and training (Bucchiarone et al., 2021; Cosentino et al., 2017; Dicheva et al., 2019; Kim et al., 2018; Lee & Hammer, 2011), everyday challenges (Vassileva, 2012), and so forth.

As highly motivating, gamification has often been implemented to promote behavior change approaches or to support positive behaviors (Casals et al., 2017) in different domains, such as transportation and mobility (Ferron et al., 2019; Yen et al., 2019), health, well-being and

* Corresponding author at: Department of Psychology and Cognitive Science, University of Trento, Trento, Via Guido Rossa 473, 51100 Pistoia (PT), Italy.
E-mail addresses: simone.bassanelli@unitn.it (S. Bassanelli), nicola.vasta@unitn.it (N. Vasta), bucchiarone@fbk.eu (A. Bucchiarone), marconi@fbk.eu (A. Marconi).

https://doi.org/10.1016/j.actpsy.2022.103657
Received 18 January 2022; Received in revised form 20 June 2022; Accepted 21 June 2022
Available online 26 June 2022

physical exercise (Chow et al., 2020; D. Johnson et al., 2016), ecology and pro-environment behaviors (Wolf, 2020), culture and tourism (Xu et al., 2016), and so forth. For example, Ferron et al. (2019) developed a gamified software to promote behavior change for sustainable mobility: in their experiment, 635 active players tracked 54,293 trips on sustainable transportation, corresponding to 244,394 sustainable kilometres, reporting a behavior change toward transportation.

Despite the attempts of several organizations to unify and coordinate the scientific community (i.e. GamiFIN[1], ACM SIGCHI[2], Gamification Europe[3]), there is still a lot of work to do to reach this goal. The main issue is that gamification documents are clustered within different domains, contributing to different parallel and isolated developments. In literature, there are several scientometric and bibliometric reviews about gamification which give us an accurate description of the gamification literature texture - i.e. Chacon et al. (2019); Flandoli and Romero-Riano (2020); Grossek et al. (2020); Lopez-Belmonte et al. (2020); Marti-Parreno et al. (2016); Segura-Robles (2019); Weiss (2019) -, but none of them focused on the existing research works applying gamification for promoting a change toward positive behaviors.

Scientometrics[4] can help us identify the structure behind the literature, measuring research quality and the impact, by providing a map of the scientific field, and measuring the scientific impact of documents. An analysis of the structure of every field of gamification is necessary since it is a relatively new topic, and a shared field between different domains. Moreover, according to Koivisto and Hamari (2019) and Morschheuser et al. (2018), gamification research should be more context-specific, goal-oriented, and aimed at target users, and it should follow new design methods, that deviate from the traditional ones. The analysis of its application for providing behavioral changes is of crucial importance for two main reasons: (1) modifying a behavioral pattern is one of the main aspects of gamification, and (2) the development of these solutions is extremely challenging. Hence, an overview of the literature structure can be useful for (1) junior researchers approaching the study of gamification (regardless of the application domain, as one of the gamification goals is to obtain a behavior change), and (2) for senior researchers, as it synthesizes existing knowledge and provides evidence of research gaps. For example, several documents in the gamification field start with an overview of the reference literature (e.g. Buckley and Doyle (2016); Fleming et al. (2017)), suggesting the need for reference documents providing the structure of the underlying literature.

In the present study, a body of documents was identified in the Scopus[5] database. The articles, their references, the authors, and the keywords were classified by co-citation techniques - the frequency with which two or more publications, authors or keywords are referenced in another publication (C. Chen, 2016) - in the CiteSpace software[6] (C. Chen, 2014; C. Chen & Morris, 2003). Hence, the content was analyzed following network and timeline analysis. Using CiteSpace software, documents were represented graphically in interactive maps. Parameters and metrics implemented in the software estimate the impact of documents, authors, and keywords on a certain cluster or in the whole network. This is useful to identify the most influential documents, authors, and keywords over time in gamification's literature applied to behavior change and positive behaviors. Specifically, document co-citation analysis (DCA) was performed to identify the relevant documents and their contribution to the trends that gave shape to the literature of the field; author co-citation analysis (ACA) was performed to identify relevant authors and their contribution for the development of the literature; and keyword co-occurrence analysis was performed to identify relevant keywords that have contributed to the literature development.

Our aim is to provide an accurate overview of the literature's structure and to describe in a structured and systematic fashion the developments and trends behind the **gamification-related literature in the domain of behavior change**, reporting the most influential documents, authors, and keywords. Considering the aim of our research, we state the following research questions:

RQ1. What are the most influential documents in the gamification for behavior change field?
RQ2. Who are the most influential authors contributing to the research of behavior change?
RQ3. How have research trends in gamification applied to behavior modification changed over time?

The article is organized into five sections. We start with the presentation of the study protocol adopted to guide our scientometric review (see Section 2). In Section 3 we present the results according to the different analysis included in our work. We dedicate Section 4 to the discussion of the results, and to present the limitations of this study. Section 5 concludes the paper.

2. Methods

In this section, we present the method adopted in our study. It is mainly composed of two macro-steps: (1) the **Literature search** (Fig. 1) and, (2) the **Data analysis and visualization**. The following sections present all the details needed to understand the study protocol used and possibly replicate it.

2.1. Literature search

The data used for the analyses include 984 publications on gamification and its application in the field of behavior change and positive behavior published between January 1st 2012 and February 24th 2022, with 46,609 unique references downloaded from the Scopus database. The time range of publications depended uniquely on Scopus' availability and no a-priori temporal exclusion criteria was applied. From an initial pool of 1001 documents, we excluded those that were written in languages other than English and duplicates, thus arriving at a final sample of 984. The search code used was "(*TITLEABS-KEY* (*gamif**) *AND TITLE-ABS-KEY* ("*behav* change*") *OR TITLE-ABS-KEY* ("*positive behav**"))". The search terms gamif* and behav* were chosen as they take into account all possible forms derived from the root (i.e. gamif* covers also gamification, and the verb gamify in all its forms; behav* covers behavior, behavioral, behavior, and behavioral). Gamification is a recent discipline in large part because its literature is made up of book chapters and conference papers. The reason for choosing Scopus over other databases was its coverage of books, book-chapters, reference books, and scientific publications (Huang et al., 2020; Pranckute, 2021).

Fig. 2 presents the results of the frequency analysis performed on the sample, revealing the number of documents by year, the most productive institutions, authors and countries, and the subject areas.

Fig. 2a presents the total number of documents by year. Overall, an exponential growth can be observed in the research domain, except for the last year, because it refers only to January and February. The Scopus database presents only two and four publications in the first and second year respectively, reaching 30 publications after two years; they reach their highest point in 2021 with 180 publications, which correspond to the 20.1 % of the total production in the Scopus database.

Fig. 2b shows the different areas of application according to the Scopus database division. The biggest area corresponded to the computer science domain (28.9 %); this is understandable as most of the gamification is implemented in software and mobile applications. The second most frequent applications of domains are medicine, and social

[1] https://gamifinconference.com/.
[2] https://sigchi.org/.
[3] https://gamification-europe.com/.
[4] https://en.wikipedia.org/wiki/Scientometrics.
[5] https://www.scopus.com/.
[6] http://cluster.cis.drexel.edu/cchen/citespace/.

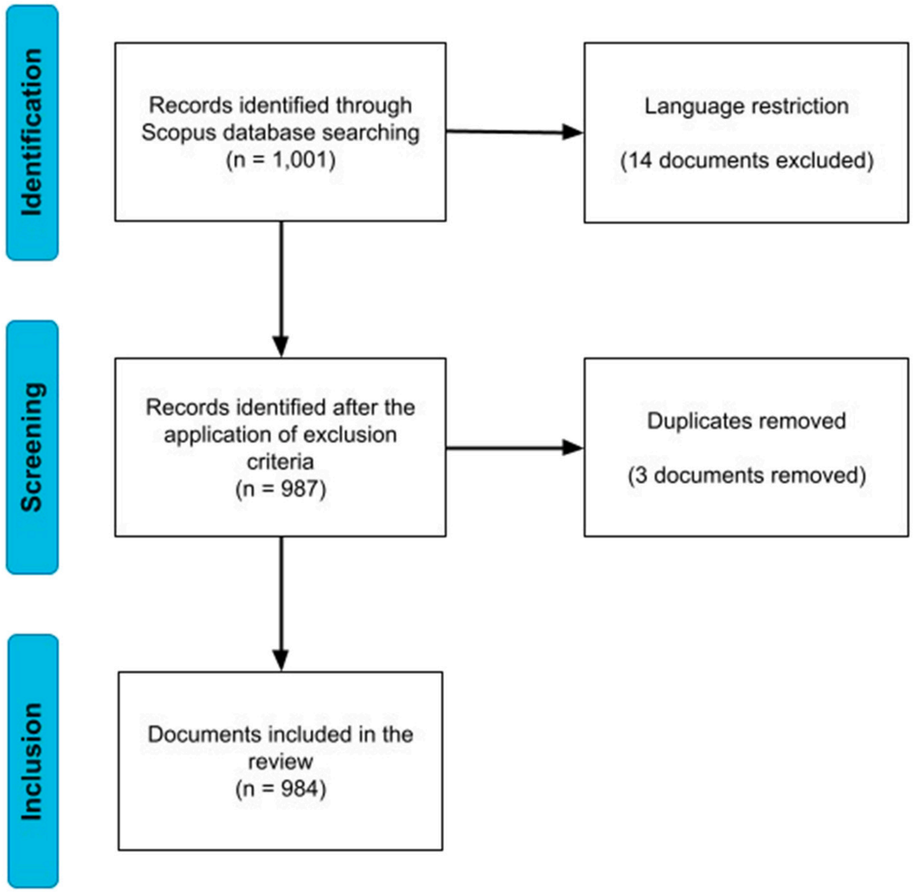


Fig. 1. Prisma diagram of the literature search.

sciences (12.7 % each), followed by engineering (10.9 %), and mathematics (7 %). Other areas of application are business, management and accounting (4.8 %), psychology (3.4 %), decision sciences, and environmental science (2.9 % each), and energy (2.7 %).

Fig. 2c presents the 10 most productive authors. J. Hamari is the most prolific with 15 publications, followed by R. Orji and A. Marconi with 14 and 13 publications respectively. Other prolific authors are M. S. Patel (10 documents), P. Fraternali (9 documents), J. Vassileva (9 documents), J. Novak (8 documents), A. E. Rizzoli (8 documents), F. Celina (7 documents), and L. E. Nacke (7 documents).

Fig. 2d presents the most prolific countries. The first in appearance was the United States (167 documents), followed by United Kingdom (119 documents), Germany (96 documents), and Australia (69 documents). Other prolific countries are Spain (65 documents), Italy (61 documents), Canada (56 documents), Netherlands (45 documents), Switzerland (45 documents), and Finland (42 documents).

Fig. 2e presents the 10 most productive institutions. Tampere University is the most prolific with 16 documents, followed by University of Pennsylvania, VA Medical Center, and Fondazione Bruno Kessler with 15 documents each. Other prolific institutions are Queensland University of Technology and The University of Oulu (14 documents each), Politecnico di Milano (13 documents), University of Pennsylvania Perelman School of Medicine, The University of Auckland, and The University of Waterloo (with 12 documents each).

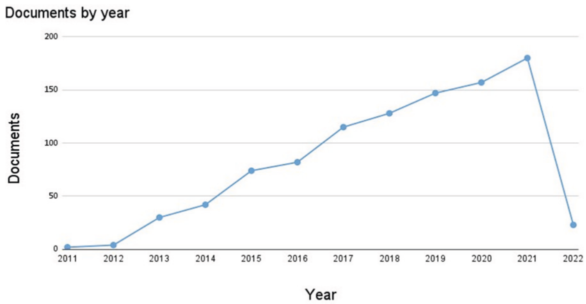
2.2. Data analysis and visualization

The data from the Scopus database were converted to a CiteSpace-friendly format (C. Chen, 2014) with the information related to each of the 984 publications retrieved. At this point, we used the CiteSpace software (version 5.8.R3) to analyze the data. Of the total references cited, 44,682 of the 46,609 (95 %) were considered valid. A small loss of references is due to data irregularities that cannot be processed by CiteSpace. This percentage of unprocessed references can be considered as a negligible loss of data (C. Chen, 2016).

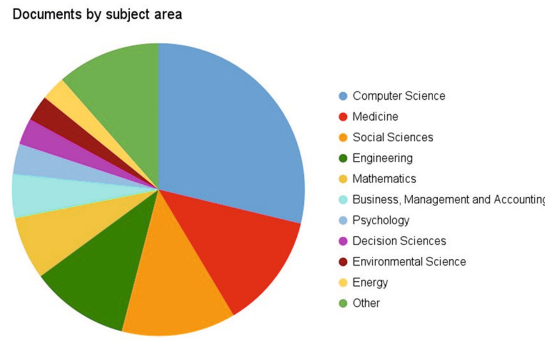
2.2.1. Settings

To generate and analyze the networks with CiteSpace, we set no time span, with the time slicing outline at one per year. We compared three criteria for node selection to identify the optimal DCA, ACA, and keyword analysis networks: Top N, Top N%, and g-index. Top N function picks up the N most cited articles and uses information from them to form the network for each time slice. Top N% includes the Top N% most cited articles in each time slice to construct the network. G-index is an improvement of the h-index that allows one to measure the global citation performance of a set of articles. It is the "*(unique) largest number such that the top g articles received (together) at least g^2 citations*" (Egghe, 2006). The networks built with Top N with N at 50 and 25, Top N% with N at 5 and 10, and g-index with a scaling factor at 10 and 25 were compared.

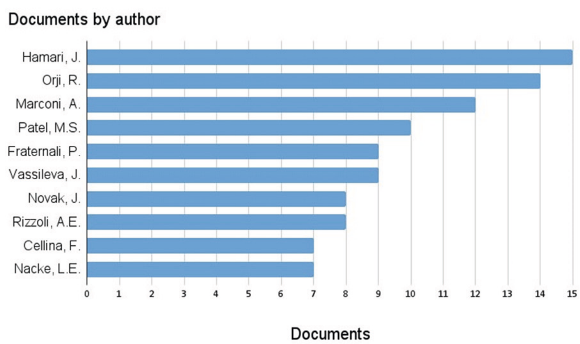
Overall, we selected the networks with Top N at 25 for DCA and keyword analysis, and Top N at 50 for ACA, since they provided better overall effects on the network's structural metrics, number of nodes and links, and a major consistency in the cluster structure for DCA. Furthermore, to obtain the best network possible, we set CiteSpace parameters "*Link Retaining Factor*" and "*Maximum Links per node*" as unlimited. After a first check, we decided to set "*Look back years*" as "*100*" to remove the few outlier values related to few internet sites references with wrong temporal information, leading to alterations in the timeline representation. The selected network for each analysis refers to the



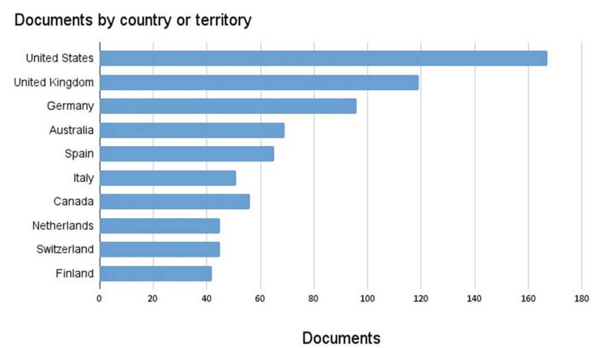
(a) Number of documents per year from January 1st 2012 to February 24th 2022.



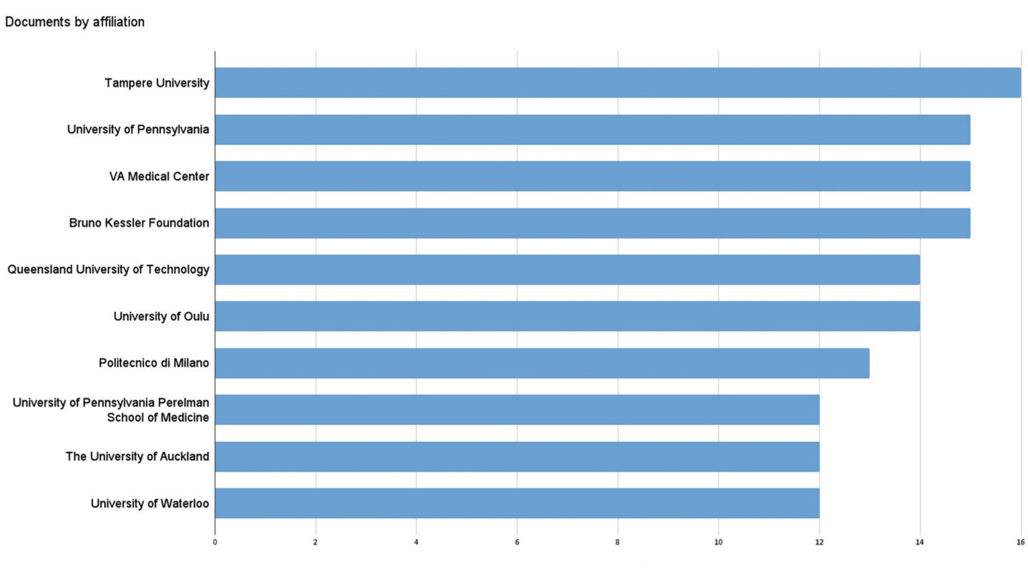
(b) Subject area.



(c) Number of documents by author.



(d) Number of documents by country.



(e) Number of documents by affiliation.

Fig. 2. Analysis of the Scopus search.
(a) Number of documents per year from January 1st 2012 to February 24th 2022.
(b) Subject area.
(c) Number of documents by author.
(d) Number of documents by country.
(e) Number of documents by affiliation.

largest connected component, that is the largest subnetwork in which you can start from any node and reach any other node (C. Chen, 2016).

2.2.2. *Analysis*

Document co-citation analysis (DCA) was performed to examine the frequency in which multiple documents have been cited together in later publications (Aryadoust, 2020; Carollo, Bonassi, et al., 2021; C. Chen et al., 2008). The study of co-citation networks focuses on interpreting the nature of clusters of co-cited documents (C. Chen et al., 2010). If two documents receive high co-citations, they can be thematically connected with each other (Bar-Ilan, 2008). Author co-citation analysis (ACA) was performed to identify the times authors were cited together. It allows identification of higher-order connectivity patterns between authors (C. Chen et al., 2008). Keywords analysis was carried out to detect the most influential keywords and their change over time. It can provide information about the core content of the articles (X. Chen & Liu, 2020); analysis of keywords and their co-occurrence can help us find hot and cutting-edge topics (Xie, 2015). Besides producing a cluster view, CiteSpace software can also generate a timeline view. For all the analysis mentioned before, this provides co-citation information as a function of the time sequence (Xie, 2015).

2.2.3. Metrics

To examine the properties of the networks and clusters, several temporal and structural metrics of co-citation were adopted. The parameters considered to detect the structural quality of the network were betweenness centrality, modularity Q index and average silhouette; while citation burstness, and sigma (Σ) were considered temporal and hybrid metrics (Carollo, Bonassi, et al., 2021; Chen, 2014; Chen et al., 2009, 2010).

2.2.3.1. Betweenness centrality. The betweenness centrality is defined for each node in the network. It measures the extent to which the node is part of a path that connects other nodes in the network (C. Chen et al., 2010; Freeman, 1977). Hence, it describes the degree in which a single node works as a bridge to connect other nodes, which would otherwise be separate (Carollo, Bonassi, et al., 2021). Betweenness centrality values range from 0 to 1, where high values (close to 1) identify a node connecting two or more large groups of nodes (Gaggero et al., 2020). Hence, high values can identify documents or journals with great influence in the network.

2.2.3.2. Modularity Q index. The modularity of a network measures the extent to which a network can be divided into modules. It has a range from 0 to 1, where low values (close to 0) suggest that the network cannot be reduced to clusters with clear boundaries. Instead, high values (over 0.7) refer to a structured network, clearly divided into distinct groups. Values close to one can suggest that components are simply isolated from one another (Aryadoust et al., 2019; Carollo, Bonassi, et al., 2021; C. Chen et al., 2010; Gaggero et al., 2020).

2.2.3.3. Silhouette. The silhouette score indicates the homogeneity of a cluster. Its value ranges between −1 and 1. A high value (over 0.7) indicates that a cluster can be considered internally consistent and distinct from other clusters; a medium value (0.5) indicates that the clustering result is reasonable. Values close to zero indicate that the objects in a cluster are on or very close to the decision boundary between two neighboring clusters. Instead, negative values indicate that cluster elements might have been assigned to the wrong cluster (Carollo, Bonassi, et al., 2021; C. Chen et al., 2010; Rousseeuw, 1987; Zhou et al., 2019). There are two ways in which silhouette can be adopted: (1) to measure the homogeneity of a cluster, and (2) to estimate the partition of the network (average silhouette score) (Aryadoust et al., 2021).

2.2.3.4. Burstness. The burstness refers to a sudden increase of the number of citations for a node during a short time interval within the overall time period (C. Chen et al., 2010; Kleinberg, 2003). Thus, this metric reflects a suddenly increasing research attention toward a publication within a specific period of time. (Aryadoust et al., 2019).

2.2.3.5. Sigma. Sigma (Σ) is a measure for scientific novelty. It comes from the combination of betweenness centrality and citation burstness: it is computed with the equation $\Sigma = (centrality + 1)^{burstness}$. High sigma values indicate works with higher influential potential, that have not only a strategically important structural property but also special temporal implication (C. Chen, 2016; C. Chen et al., 2009, 2010; Gaggero et al., 2020).

2.2.4. Clustering

We used the clustering function in CiteSpace in order to identify clusters of documents for DCA. The algorithm is able to create clusters of publications by considering the strength of connections between cited and citing documents. Cluster labels are selected from noun phrases and index terms following three different algorithms: Log-Likelihood Ratio (LLR) (C. Chen, 2014), Mutual Information (MI) (Zheng, 2019), and Latent Semantic Indexing (LSI) (Deerwester et al., 1990). The three algorithms use different methods to identify the cluster themes. LSI uses document matrices (C. Chen, 2014); while both LLR and MI identify cluster themes by indexing noun phrases in the abstracts of citing articles (C. Chen et al., 2010). Cluster labeling was conducted automatically using all the three algorithms. After a first check, we decided to use the LLR algorithm to compare the occurrences of terms in the citing articles. The cluster obtained through the LLR algorithm were numbered in descending order according to their cluster size. This approach is supported by the software creator (C. Chen, 2014), since the cluster labeling LLR provides the best results in unique labeling with sufficient coverage. The labels obtained were checked by experts in order to modify duplicate or unsuitable labels (i.e. labels that did not match the content of the cluster). A detailed description of this renaming process can be found in the "Results" section, within the "Document co-citation analysis" subsection. Next, we used two different CiteSpace visualizations methods: the cluster view, which displays a spatial representation of the diagram (Fig. 3), and the timeline view, which displays a network by arranging its clusters along horizontal timelines. In the cluster view, the thickness of the node reflects the amount of cited references inside the clusters. The passage of time is represented with the color shading from the oldest (purplish) to the newest (yellowish). In addition, multi-colored rings reflect the burstness (red) and betweenness centrality (purple). In the timeline view, the major clusters are arranged in a horizontal timeline, in which the oldest nodes are placed on the left of the timeline, while the newests are placed on the right part of the timeline. Items in the timeline are connected with a link, whose thickness is proportional to the strength of co-citation.

3. Results

In this section, we provide a set of results according to the adopted metrics for each CiteSpace analysis used. Hence, we describe each cluster found through cluster analysis.

3.1. Document co-citation analysis (DCA)

The DCA provided a network with 922 nodes and 18,602 links, showing a modularity Q index of 0.8561 and an average silhouette metric of 0.9649, suggesting that the network was sufficiently divisible into clusters (according to the Q index) and that each cluster was highly consistent (according to the silhouette index) (Fig. 3).

DCA resulted in the identification of 18 co-citation clusters (Table 1) sorted from the largest in size (cluster #0 = "Evaluating behavior change intervention", size = 142, silhouette = 0.861, mean year = 2010) to the smallest (cluster #12 = "Persuasive mobile application", size = 6, silhouette = 0.991, mean year = 2010).

Since some of the clusters identified through the DCA were not substantial enough, we chose to present in detail only the 7 major clusters generated through the "generate narrative" command. In addition, in accordance with Aryadoust et al. (2021), emphasizing the importance of considering clusters counter-label based on the evaluation of the documents within each cluster, we chose to rename cluster #5 "Evaluating behavior change intervention" in "Student behavior" and cluster #6 "Human nature" in "Fun belief" (a detailed description of the rationale for these changes will be performed below, during the

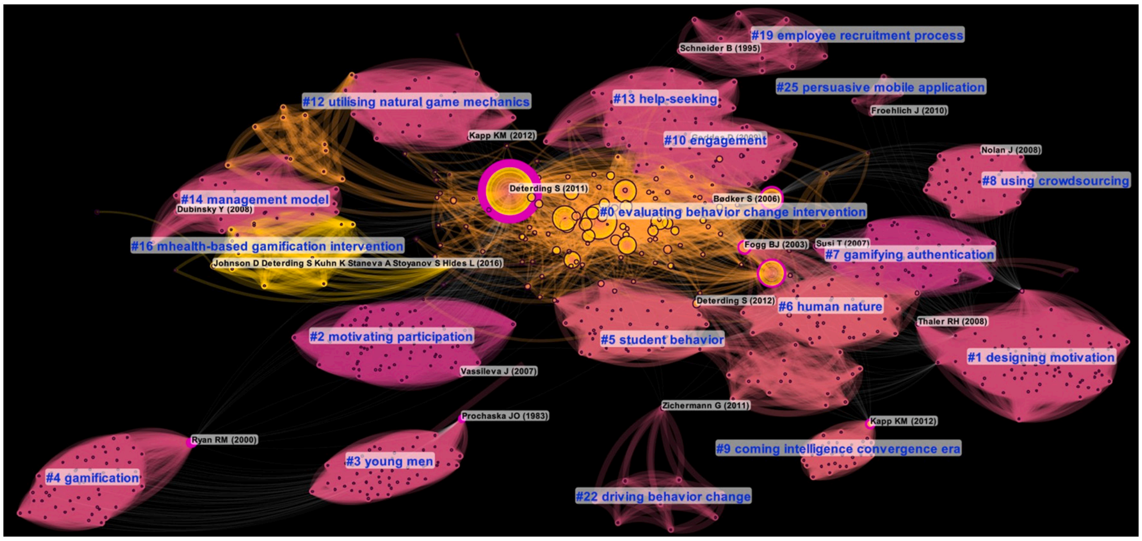


Fig. 3. Cluster view of the document co-citation analysis (DCA) generated using CiteSpace Version 5.8.R3. Modularity Q = 0.8561; average silhouette = 0.9649. Colored shades indicate the passage of time, from past (purplish) to the present time (yellowish). Colored tree rings refer to the nodes with high betweenness centrality (purple tree rings) and burstness (red tree rings). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Cluster labels computed via document co-citation analysis (DCA).

Cluster ID	Cluster label	Size	Silhouette	Mean (year)	Begin	End	Duration
0	Evaluating behavior change intervention	142	0.861	2010	1977	2019	42
1	Designing motivation	79	0.995	2008	1968	2011	43
2	Motivating participation	79	0.995	2003	1954	2012	58
3	Young men	61	1	2006	1961	2012	51
4	Gamification	57	0.988	2011	1988	2013	25
5	Student behavior	55	0.955	2007	1980	2012	32
6	Fun belief	44	0.968	2010	1955	2012	57

description of the individual clusters).

Among the 7 major clusters, the duration ranged from 25 to 58 years, presenting several overlaps. Cluster #2 = "Motivating participation" has the higher duration over time (58 years), followed by cluster #6 = "Fun belief" (previously "Human nature") (64 years) and cluster #3 = "Young men" (51 years). Cluster #4 = "Gamification" has the smallest duration over time (25 years). By looking at publication mean year, cluster #2 seems to be the oldest one (mean year = 2003), while cluster #0 = "Evaluating behavior change intervention" (mean year = 2010), cluster #4 (mean year = 2011) and cluster #6 (mean year = 2010) the most recent ones.

However, it is worth noting that the mean year of publication of some clusters may have been largely biased by older publications. For example, cluster #2's mean year of publication is 2003, but this cluster is among those with a longer duration (58 years, from 1954 to 2012) and bigger size (79). Since mean is extremely affected by extreme values, older papers, even if few, may have drastically lowered the publication mean year reported by CiteSpace. For this reason, we chose to group and describe clusters by sorting them by size (i.e., by the number of cited documents in each cluster) (Table 1), rather than by year.

Below, the 7 major clusters found through the "generate narratives" command are presented and described.

Cluster #0, "Evaluating behavior change intervention" is the biggest one in size, but also the less homogenous (silhouette = 0.861) among the 7 major clusters. It contains 142 cited documents written between 1977 and 2019 (mean year = 2010), some of which contributed to the definition and the development of the gamification domain. This cluster focuses mostly on describing the strengths and the weaknesses of gamification applied to behavioral change. It also collects early and recent cited documents on gamification and its application to different domains (mainly education, health and environmental awareness), from both a theoretical and applied point of view. The cluster name is in line with the scope of interest of this review and suggests that the citing documents within this cluster refer mainly to the evaluation of behavior change intervention programs. Although the citing documents do not always directly address gamification, it is interesting to note that the three cited documents with the highest citation frequency explicitly refer to gamification. The citing document with the greatest coverage (i.e., the one that cited more references in the cluster) is Trinidad et al. (2021) with 18 citations, while the cited documents with the highest citation frequency are Deterding, Dixon, et al. (2011) with a frequency of 210, Hamari et al. (2014) with a frequency of 144, Seaborn and Fels (2015) with a frequency of 73 and McGonigal (2011) with a frequency of 61.

Cluster #1, "Designing motivation" and **Cluster #2**, "Motivating participation" both have a size of 79 cited references, with the former ranging from 1968 to 2011 and the latter ranging from 1954 to 2012. Both clusters contain cited documents that attempt to explore the importance of motivation in behavior change interventions, with more theoretical and design-oriented documents in cluster #1 and more applied documents in cluster #2. It is interesting to note that most of the cited documents in these clusters are prior to 2011 (when gamification was mentioned for the first time) and do not refer explicitly to gamification. Moreover, these two clusters draw their name from few citing documents (4 citing documents for cluster #1 and only one for cluster #2) suggesting that the literature tends to remain anchored to few theoretical papers. In cluster #1 the citing document with the greatest coverage is Nakajima and Lehdonvirta (2013) with 79 citations, while the three most influential cited references are Leonard (2008) with a frequency of 5 citations, Fogg (2002) with a frequency of 4 and Reeves and Read (2009) with a frequency of 4. In cluster #2, all cited documents show a citation frequency equal to one, as the cluster consists of only one citing document, namely Vassileva (2012).

Cluster #3, "Young men", contains 61 cited references written between 1961 and 2012 (mean year = 2006). It is mainly composed of cited documents that aim to promote gamified physical activity programs in young participants. Like cluster #2, cluster #3 consists of a single citing document, namely Ahola et al. (2013), which therefore contains all the cited documents with a citation frequency of one. The fact that only one citing document makes up the cluster suggests that Ahola et al. (2013) is a document of relevance in the literature, while the cluster name suggests that gamified programs often have young participants as their target audience.

Cluster #4, "Gamification", has a size of 57 cited documents from 1988 to 2013 and it is the most recent one according to the mean year (2011). Among the other clusters, it is also the shortest in terms of duration (25 years). It collects several cited documents involving behavioral change protocols, gamification and gamification applied to behavioral changes. The cluster consists of only two citing documents, namely Schoech et al. (2013) and Putz and Treiblmaier (2015), both of which are theoretical documents on the application of gamification to different domains. The only cited document that emerges in this cluster is (Ryan & Deci, 2000) with a citation frequency of 5, while the remaining show a frequency of one.

Cluster #5, "Student behavior" (previously "Evaluating behavior change intervention"), has a size of 55 cited references, written from 1980 to 2012 (mean year = 2007). Cited documents included in this cluster involve mostly gamification applied to education programs or theoretical works on gamification in general. By looking at the citing and cited documents, it was noted that the cluster name "Evaluating behavior change intervention" was redundant (as it was identical to cluster #0 name) and not precise, while the name "Student behavior" allowed for a more accurate capture of the cluster core focus, as several documents involved exploring students behavior. Thus, the cluster name was changed. Here, the citing document with the greatest coverage is Rao (2013) with 36 citations, while the cited documents with the highest citation frequency are Deterding (2012) with a frequency of 17 and Baranowski et al. (2008) with a frequency of 10.

Cluster #6, "Fun belief" (previously "Human nature"), contains 44 cited references written between 1955 and 2012 (mean year = 2010). Most of its cited documents are related to persuasive techniques, gaming and gamification. The cluster name was changed to "Fun belief" since "Human nature" was vague and not really informative of the cluster content, while "Fun belief" represented the cluster more accurately. Its citing document with the greatest coverage is Whitson (2013) with 42 citations, while the most influential cited documents are Fogg (2002) with a citation frequency of 22, and Tekinbas and Zimmerman (2003) with a citation frequency of 5.

Through DCA, we computed the major 25 citation bursts; Table 2 reports the strongest 10. The publication of Deterding, Sicart, et al. (2011) has the strongest burst of the network, with a strength of 16.41, and it was the burst with the longest duration over time (4 years) along with the publication of Zichermann and Cunningham (2011). The oldest bursts in the network started in 2014 (McGonigal, 2011; Zichermann & Cunningham, 2011), while the newest started in 2020 (Koivisto & Hamari, 2019; Sailer et al., 2017). Interestingly, all the main citation bursts are contained within the cluster #0, suggesting that this cluster collects all the documents that have attracted research attention the most.

Among our network, the publication of Deterding, Dixon, et al. (2011) has a sigma value higher than the other publications (7055.67), followed by Zichermann and Cunningham (2011) (5.90), McGonigal (2011) (4.63), and Fogg (2002) (2.30). The other values do not differ so much from 1. Instead, regarding the values for the betweenness centrality, publications range from 0 to 0.72 (Table 3). The highest value is the publication of Deterding, Dixon, et al. (2011).

3.2. *Author co-citation analysis (ACA)*

By analyzing author co-citation analysis, we can find influential authors in the field of gamification applied to behavior change. The magnitude of each node represents author's citation counts and the length between two nodes represents the two author co-citation frequency. A bigger node suggests an important author for the network; a smaller distance between two nodes detect a high authors' co-citation frequency, and a closer research topic and direction (X. Chen & Liu, 2020). The network obtained through the ACA contains 857 authors and 20,433 collaboration links (Fig. 4), showing a modularity Q index of 0.7988, and an average silhouette metric of 0.936. The network has a wide range of collaborations, which reflects the interdisciplinary nature of gamification and the several domains in which behavior change can be utilized.

Table 4 shows the top 10 authors according to citation frequency. The largest node represents the author Deterding S with a citation frequency of 401 and a centrality value of 0.61, followed by Hamari J with a citation frequency of 289 and a centrality of 0.01. The third author ordered by citation frequency is [Anonymous] which is not of interest because this might be due to missing names of the authors of some publications in the Scopus dataset or due to loss of information during the conversion of the Scopus files. Since it is considered an outlier, we decided to ignore it.

Table 3
Top 5 documents for betweenness centrality via document co-citation analysis (DCA).

Reference	Centrality	Cluster ID
Deterding, Dixon, et al. (2011)	0.72	0
Ryan and Deci (2000)	0.37	0
Prochaska and DiClemente (1983)	0.21	3
McGonigal (2011)	0.17	0
Zichermann and Cunningham (2011)	0.17	0

Table 2
List of the top 10 documents for burst strength, estimated via document co-citation analysis (DCA).

Reference	Burst strength	Burst begin	Burst end	Centrality	Sigma	Cluster ID
Deterding, Dixon, et al. (2011)	16.41	2015	2019	0.72	7055.67	0
Koivisto and Hamari (2019)	14.91	2020	2022	0.00	1.01	0
Hamari et al. (2014)	12.83	2016	2019	0.04	1.64	0
Seaborn and Fels (2015)	12.21	2019	2022	0.01	1.14	0
Zichermann and Cunningham (2011)	11.05	2014	2018	0.17	5.90	0
McGonigal (2011)	9.67	2014	2017	0.17	4.63	0
D. Johnson et al., 2016	9.66	2019	2022	0.00	1.02	0
Hamari (2017)	8.61	2019	2022	0.00	1.03	0
Sailer et al. (2017)	8.14	2020	2022	0.00	1.02	0
Huotari and Hamari (2017)	8.02	2019	2022	0.00	1.02	0

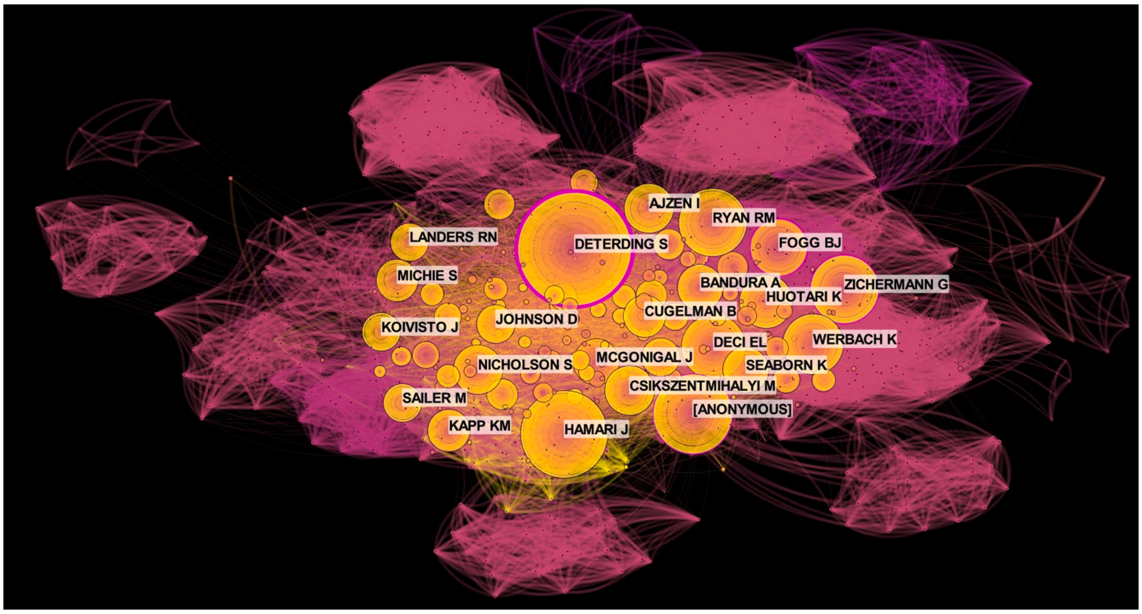


Fig. 4. A visualization of the author co-citation analysis generated using CiteSpace Version 5.8.R3. Modularity Q = 0.7988; average silhouette = 0.936.

Table 4
Top 10 cited authors ordered by citation frequency via author co-citation analysis (ACA).

Authors	Frequency	Centrality
Deterding S	401	0.61
Hamari J	289	0.01
[Anonymous]	166	0.13
Ryan RM	131	0.04
Deci EL	119	0.05
Zichermann G	118	0.17
Werbach K	102	0.01
Fogg BJ	96	0.17
Seaborn K	95	0.01
Huotari K	89	0.03

Table 5 presents the top 10 ranking authors according to burstness computed via ACA. The author with the highest burst strength was Koivisto J (strength = 14.42, centrality = 0.01), whose burstness started in 2020 and ended in 2022, followed by Morschheuser B (strength = 10.29, centrality = 0.00, 2019–2022) and Johnson D (strength = 10.05, centrality 0.00, 2019–2022). However, the increasing trend in citations for the cited authors listed in Table 5 ended in 2022 (except Oinas-Kukkonen H, which burst ended in 2019), which is the year this review was written, suggesting that their burst strength is likely to continue for the foreseeable future.

Table 5
Top 10 author bursts computed via author co-citation analysis (ACA).

Cited authors	Burst strength	Begin	End	Span	Centrality	Frequency
Koivisto J	14.42	2020	2022	2	0.01	83
Morschheuser B	10.29	2019	2022	3	0.00	36
Johnson D	10.05	2019	2022	3	0.00	74
Landers RN	10.04	2020	2022	2	0.00	67
Sailer M	9.24	2020	2022	2	0.00	62
Sardi L	8.84	2019	2022	3	0.00	35
Dichev C	8.34	2020	2022	2	0.00	19
Oinas-Kukkonen H	7.82	2017	2019	2	0.00	41
Cohen J	7.20	2020	2022	2	0.01	28
Edwards EA	7.09	2018	2022	4	0.00	30

3.3. Keyword co-occurrence analysis

The keyword co-occurrence analysis is an important aid to explain the structure of scientific knowledge and discover research trends (Su et al., 2019). The detection of keywords refers to the words that are frequently used or that are used in a shorter period. The keyword co-occurrence analysis provided a network with 325 nodes and 3965 links, showing a modularity Q index of 0.5087 and a weighted mean silhouette of 0.8698.

Table 6 lists the top 10 keywords with the strongest bursts. In terms of burst strength, the top ranked keyword is “education” with a burst of 9.13, followed by “health” with a burst of 8.12, “behavioural change” with a burst of 7.42, “behavioral change” with a burst of 6.93 and “serious game” with a burst of 6.70. “Persuasive technology”, “design”, “sustainable development”, and “intrinsic motivation” have the earliest burst begin, while “major clinical study”, “controlled study”, “randomized controlled trial”, “sustainability” and “article” have the latest burst begin, which is over in 2022 because it was the date of our search. It is legitimate to think that it could continue in the future years, increasing the duration time.

According to the beginning and the end of the burst, we can discover the change over time for the topics in the field. In the early stages, “Persuasive technology”, “design”, “sustainable development”, and “intrinsic motivation” are the mainstream trends, followed by “health”, “health promotion”, “game based learning”, “education”, “human computer interaction”, and “video game”. After them, “behavioral change”, “behavioural change”, “serious game”, “energy conservation”,

Table 6
Top 10 keyword bursts computed via keyword analysis.

Keywords	Strength	Begin	End	Duration
Education	9.13	2015	2017	2
Health	8.12	2014	2017	3
Behavioural change	7.42	2016	2019	3
Behavioral change	6.93	2017	2019	2
Serious game	6.70	2016	2018	2
Major clinical study	6.54	2019	2022	3
Energy conservation	6.35	2017	2018	1
Sustainability	6.06	2020	2022	2
Human computer interaction	5.99	2015	2017	2
Design	5.79	2013	2016	3

"health behavior", and "psychology" have become the trends in the literature. However, "major clinical study", "controlled study", "randomized controlled trial", and "sustainability" have become the research frontier in recent years.

4. Discussion

In this section we answer the research questions we initially defined. Our aim is to provide a structured and systematic description of gamification's literature applied to behavior change. Thus, we outlined the main outcomes we found during the analysis and we propose some directions for future studies. In each section, a single research question is discussed based on the findings described in the Results section.

4.1. What are the most influential documents in the gamification for behavior change field?

To answer this question, we focused on DCA only, since it contains all the information needed to respond. Here, to extrapolate the most influential documents we followed two different ways: (1) on the one hand we looked at documents with higher burst strength, betweenness centrality and sigma values (Tables 2, 3), as burstness reflect a sudden research interest during a limited period of time, betweenness centrality reflect the influence on the network and sigma is a combination of these two measures (see the Methods section for a detailed description); (2) on the other hand we took the top cited and citing documents contained in the clusters with higher size (Table 1).

Considering burst strength, betweenness centrality and sigma values, the paper that has attracted the most research attention and that has influenced the literature network is definitely Deterding, Dixon, et al. (2011), with the first place in both burst strength (16.41) and betweenness centrality (centrality = 0.72), and with a sigma value significantly higher than the other documents (sigma = 7055.67). This document is the first paper that defined the concept of "gamification", describing the design of a typical gamified paradigm and focusing on gamification historical origins and applications. According to our review, it has been a cornerstone paper in the field of gamification applied to behavioral change and it stands as a guideline for subsequent gamification works. However, its citation peak has ended in 2019 (burst started in 2015 and ended in 2019), suggesting that Deterding, Dixon, et al. (2011) has been a popular document in this field for some years, but has recently been overlooked.

In contrast, citations bursts of Koivisto and Hamari (2019) and Seaborn and Fels (2015), ranked second (14.91) and fourth (12.21) in terms of burst strength respectively, began in a relatively more recent year (2020 and 2019) and may not have ended yet (bursts ended in 2022, which is the year this review was written). In detail, Koivisto and Hamari (2019) consists of a large systematic review on 819 empirical studies that employed gamification, while Seaborn and Fels (2015) aims to conduct an impressive review outlining the theoretical understandings of gamification and comparing gamification with other methodologies (such as alternate reality games, games with a purpose, and gameful design). Finally, at the third place in terms of burst strength we found Hamari et al. (2014), with a burst of 12.83 (burst began in 2016 and ended in 2019). This document consists of a large review on the effectiveness of gamification when applied to different domains. Looking at betweenness centrality, in first place we find (as already reported) Deterding, Dixon, et al. (2011) (centrality = 0.72), followed by Ryan and Deci (2000) (centrality = 0.37), next Prochaska and DiClemente (1983) (centrality = 0.21), McGonigal (2011) (centrality = 0.17), and finally Zichermann and Cunningham (2011) (centrality = 0.17). Thus, Deterding, Dixon, et al. (2011) is also the document with the highest influence on the network of documents selected for this review. Interestingly, only Prochaska and DiClemente (1983) describes an empirical study, while Ryan and Deci (2000) is a review, and both McGonigal (2011) and Zichermann and Cunningham (2011) are books. This might have affected their top rankings in betweenness centrality: since books and reviews (generally) contain more information than scientific papers, they are very likely to be cited more and in more domains. Moreover, Zichermann and Cunningham (2011) and McGonigal (2011) show the second (5.90) and third (4.63) highest sigma values respectively, suggesting that they are works with a high influential potential on the topic (C. Chen et al. (2009, 2010)).

Considering the top cited and citing documents within the four largest size clusters, we find Deterding, Dixon, et al. (2011) and Hamari et al. (2014) as the most cited documents in cluster #0 (i.e., the cluster with the largest size), with 210 citations the former and 114 the latter, and Trinidad et al. (2021) as the citing document with the largest coverage (18). These documents are respectively a conference paper, a review and a bibliometric analysis, focusing on both theoretical and applied aspects of gamification. Therefore, it is not surprising that they have been grouped in cluster #0, which collects the most important documents concerning general theoretical and applicative information on the gamification domain applied to behavior change. In cluster #1, Leonard (2008) and Fogg (2002) are the cited documents with the higher citation frequency, 5 and 4 respectively, while Nakajima and Lehdonvirta (2013) is the citing document with the greatest coverage (79). Leonard (2008) and Fogg (2002) are both prior to 2011 and they don't address gamification directly. They are respectively a comment on a book about nudging and a book chapter on persuasive techniques. On the other hand, Nakajima and Lehdonvirta (2013) describes four case studies that employed gamified persuasive technologies for behavior change.

Clusters #2 and #3 are both composed of a single citing document, thus each cited document within each cluster has a citation frequency equal to one. This fact, in our opinion, points out that the literature in the domain of gamification applied to behavior change sometimes tends to remain anchored to few theoretical papers and struggle to build a comprehensive network. In cluster #2, the citing document that collects all the cited documents of the cluster is Vassileva (2012). This paper describes several different approaches to motivate people engaging in behavioral change programs. In cluster #3, Ahola et al. (2013) is the only citing document: it consists of a paper describing a massive study in which 1500 young men undergo a 6-months online gamified activation method in order to change their behavior.

Interestingly, the most important documents in the field of gamification applied to behavior change are almost never papers about original experimental studies (apart from few studies, such as Ahola et al. (2013) and Prochaska and DiClemente (1983)). This seems to suggest that this field possesses some strong theoretical works (mainly books and reviews), but lacks corroborated experimental support. Future studies should focus more on this second aspect.

4.2. Who are the most influential authors contributing to the research of behavior change?

To address this research question, we rely on the results of the ACA. Tables 4 and 5 give us an overview on the most influential authors according to citation frequency and burst strength.

Considering burst strength, the author who attracted the most research attention over a period of time is Koivisto J (burst strength = 14.42). This author's burst is probably linked to the review Koivisto and Hamari (2019), which is also the second document for burst strength. Since the burst ends in 2022 (date of the review), it is legitimate to think that it could continue in the future years, increasing the duration time. This can mean Koivisto J is helping in shaping the recent and future part of the literature. In the second place in terms of burst strength, we find Morschheuser B (burst strength = 10.29). His documents deal with gamification design (Morschheuser et al., 2018; Morschheuser, Hamari, Koivisto, & Maedche, 2017; Morschheuser, Hamari, Werder, & Abe, 2017). His burst strength started in 2019, and ended in 2022. Also in this case we can think that the burst continues beyond the date. In the third and fourth place in terms of burst strength, we find Johnson D (burst strength = 10.05), whose most cited documents (C. Johnson et al., 2016; D. Johnson et al., 2016; Johnson et al., 2017) deals with the use of gamified solutions to motivate users to adopt behaviors related to health and well-being, and to the reduction of domestic energy consumption, and Landers RN (burst strength = 10.04), whose publications deal with gamification theory (Landers, 2014; Landers et al., 2018), gamification use (Armstrong & Landers, 2018), and several analysis on gamification elements (Landers et al., 2017; Landers & Landers, 2014). Looking at the timeline of the most influential documents, the authors with the biggest burst strength are the most recent.

Interestingly, exploring the research fields of the most influential authors for burst strength, within the ones with the higher burst value (Koivisto J, Morschheuser B, Johnson D, and Landers RN), only Johnson D directly applied gamification to produce a behavioral change. Sorting the burst strength by the beginning year of burst, most of the authors with an old burst (Bartle L, Marczewski A, Zichermann G, McGonigal J, and Farzan R) deal with user motivation and participation, and gamification definition. Hence, more recent authors for burst (Oinas-Kukkonen H, Nacke LE, and Edwards EA) deal with gamification definition, personalization, and application in the health domain. The most recent authors according to burst begin (Morschheuser B, Johnson D, Sardi L, Koivisto J, Landers RN, Dichev C, and Cohen J) deal with the issues in gamification development, the need of novel designing methods, and the application of gamified solutions to produce behavioral changes in users.

Considering the citation frequency, the most influential authors are Deterding S (citation frequency = 401) and Hamari J (citation frequency = 289). This result is not surprising since a great amount of the most important documents in the gamification domains are written by these two authors (Deterding, 2012; Deterding, Dixon, et al., 2011; Deterding, Sicart, et al., 2011; Hamari, 2013, 2017; Hamari et al., 2014; Hamari & Koivisto, 2013; Hamari & Tuunanen, 2014; Koivisto & Hamari, 2019).

Overall, the ACA results suggest that initially the structure of gamification's literature applied to behavior change has been guided by the documents of Deterding S, Hamari J, Marczewski A, Zichermann G, McGonigal J, Farzan R, and Bartle L, resulting in an initial cohesive structure composed of theoretical documents dealing with persuasion, design and gamification definition. Next, according to the newest bursts, the current structure of gamification's literature applied to behavior change is divided into two parts depending on the main subject of the authors: (1) Morschheuser B, and Koivisto J deal with the need to question current application and design methodologies, hence finding new solutions (Koivisto & Hamari, 2019; Morschheuser et al., 2018; Morschheuser, Hamari, Werder, & Abe, 2017); (2) Johnson D, Sardi L, Cohen J, and Landers RN deal with a practical application of gamification to promote behavioral changes in users (D. Johnson et al., 2016; Johnson et al., 2017; Sardi et al., 2017).

4.3. *How have research trends in gamification applied to behavior modification changed over time?*

To answer this question, we rely on an overview of the keywords change over time and on the DCA analysis. Examining the keywords' burst strength begin year (Table 6) and the major clusters' mean years (Table 1), we managed to extrapolate a timeline of the research trends in the gamification for behavior change domain. From this analysis, it seems clear that the researchers' interest has changed over time.

According to keywords, the first trends that appeared in the field of gamification applied to behavioral change are “design” (begin year = 2013), “health” (2014), “human computer interaction” (2015) and “education” (2015). This seems to suggest that the first research trends were linked to a general design stage, mainly involving health and education domains. Hence, the trend has changed, showing interest in “serious games” (2016) and “behavioral change” - which appears twice: “behavioural change” (2016) and “behavioral change” (2017) -, thus suggesting that research attention shifted from a general theoretical design stage toward the study of gamified procedures for behavior change. Finally, the last trends are related to environmental awareness (“energy conservation”, begin year = 2017, and “sustainability”, begin year = 2020) and clinical disorders (“major clinical study”, begin year = 2019), suggesting that these trends are the most recent in the field of gamification for behavior change. Interestingly, burst's ending year of “major clinical study” and “sustainability” is 2022, reflecting the fact that the bursts may still be ongoing.

According to the DCA analysis, the oldest clusters are “motivating participation” (mean year = 2003), “young men” (2006), “student behavior” (2007) and “designing motivation” (2008). Considering the labels of these clusters and their content (in terms of cited and citing documents), it seems that the research interest in the behavior change domain has been initially focused on the study of motivational interventions designs targeting students or young subjects. On the other hand, the most recent clusters (according to our review) are “evaluating behavior change intervention” (2010), “fun belief” (2010) and “gamification” (2011), thus clusters that collect documents on behavior change interventions (mostly gamified) and both theoretical and applied studies on gamification. This suggests that, only in recent times, research has focused on studying proper gamified interventions.

Overall, these results seem to suggest that trends have changed considerably over time, first describing broad motivational intervention designs and then leading more and more resources in the direction of a unitary concept of gamification based on gamified interventions. Finally, according to the keywords analysis, it seems that the most recent trends involve gamified intervention for environmental awareness.

4.4. *Limitations*

When interpreting the results of this scientometric review, it is worth noting that there are some limitations to consider. First, only data from the Scopus database were used in this study; data from other databases such as WoS, PubMed and PsyInfo were not used. Future studies could compare other databases to decide on the more comprehensive database to use.

Second, as already observed by other authors (Carollo, Balagtas, Neoh, & Esposito, 2021; Carollo, Bonassi, et al., 2021), the scientometric approach of DCA depends on the quantitative patterns of citations and co-citations: hence, all the citations are treated the same way, leaving out the reason behind each citation.

Third, the impact of recent influential documents might have been underestimated, causing a bias toward the old ones due to their longer lifetime.

Lastly, only the names of the first authors were used in the co-citation analyses performed in this study; hence, the co-citation analysis may yield different results if all the author names were made available.

5. Conclusions

Gamification is facing a continuous growth in disparate application contexts (e.g. education, training, health, and so forth), especially in those that promote a positive behavior change (Adrian & Elena, 2019). Indeed, gaming, as a motivating and engaging activity, makes it easier to convince people to break their bad habits and change their behavior.

This study analyzed research works on gamification to promote behavior change or positive behaviors, based on publications from 2011 to 2022 available in the Scopus database. It reveals that from a small number of publications that first appeared in 2011 and 2012, the number of works related to behavior change have exponentially grown, and that the application areas are many. We performed co-citation analysis to identify the most influential documents, authors, keywords, how the documents are gathered in clusters to represent the scientific domains within the available literature, and we investigated the trends change over time.

Overall, what emerges most is that the research interest has changed slightly over time. At the beginning, it has been anchored to those keywords, authors and documents related to the self-determination theory, and methods for designing gamification as a persuasive and motivational tool. According to several recent reviews in the literature (Koivisto & Hamari, 2019; Seaborn & Fels, 2015), the failure in promoting a standard guideline, and the lack in employing adequate methodological rigor (such as sample size selection and controlled experimental research methods) has led to numerous inconsistent results with the gamification use. Hence, the research interest appears to have spread into two main areas in order to solve these problems, moving away from the first research topics: (1) the research for new solutions and new design methods, and (2) the application of gamification for promoting environmental awareness, sustainability and well-being behaviors with greater methodological rigor.

In conclusion, the results of this study suggest that, as in other scientific areas (Chambers & Tzavella, 2020; Foster & Deardorff, 2017), and in line with other gamification domains (Trinidad et al., 2021), we expect that the use of gamification for behavior change will be supported by documents aimed at suggesting new and standardized procedures for the gamification design, and documents promoting an adequate methodological rigor.

It may be useful in future to conduct scientometric studies in specific fields related to behavior change (i.e. health and well-being, environmental awareness, and sustainability). This may provide in-depth information regarding the status of gamification for providing behavior change in various fields. We hope that the findings of the present study will lead to better understanding of the topic we presented.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Adrian, S.-R., & Elena, P.-G. M. (2019). Active methodologies in health. Scientific production on ́ gamification in health sciences. *Science for Education Today, 9*(3).

Ahola, R., Pyky, R., Jamsa, T., Mantysaari, M., Koskimaki, H., Ikaheimo, T. M., & Korpelainen, R. (2013). Gamified physical activation of young men–a multidisciplinary population-based randomized controlled trial (mopo study). *BMC Public Health, 13*(1), 1–8.

Alsawaier, R. S. (2018). The effect of gamification on motivation and engagement. *The International Journal of Information and Learning Technology, 35*(1), 56–79. https://doi.org/10.1108/IJILT-02-2017-0009

Armstrong, M. B., & Landers, R. N. (2018). Gamification of employee training and development. *International Journal of Training and Development, 22*(2), 162–169.

Aryadoust, V. (2020). A review of comprehension subskills: A scientometrics perspective. *System, 88*, Article 102180.

Aryadoust, V., Tan, H. A. H., & Ng, L. Y. (2019). A scientometric review of rasch measurement: The rise and progress of a specialty. *Frontiers in Psychology, 10*, 2197.

Aryadoust, V., Zakaria, A., Lim, M. H., & Chen, C. (2021). An extensive knowledge mapping review of measurement and validity in language assessment and sla research. *Frontiers in Psychology*, 1941.

Baranowski, T., Buday, R., Thompson, D. I., & Baranowski, J. (2008). Playing for real: Video games and stories for health-related behavior change. *American Journal of Preventive Medicine, 34*(1), 74–82.

Bar-Ilan, J. (2008). Informetrics at the beginning of the 21st century—a review. *Journal of Informetrics, 2*(1), 1–52.

Bucchiarone, A., Cicchetti, A., Bassanelli, S., & Marconi, A. (2021). How to merge gamification efforts for programming and modelling: A tool implementation perspective. In *2021 ACM/IEEE international conference on model driven engineering languages and systems companion (models-c)* (pp. 721–726).

Buckley, P., & Doyle, E. (2016). Gamification and student motivation. *Interactive Learning Environments, 24*(6), 1162–1175.

Carollo, A., Balagtas, J. P. M., Neoh, M. J.-Y., & Esposito, G. (2021). A scientometric approach to review the role of the medial preoptic area (mpoa) in parental behavior. *Brain Sciences, 11*(3), 393.

Carollo, A., Bonassi, A., Lim, M., Gabrieli, G., Setoh, P., Dimitriou, D., & Esposito, G. (2021). Developmental disabilities across the world: A scientometric review from 1936 to 2020. *Research in Developmental Disabilities, 117*, Article 104031.

Casals, M., Gangolells, M., Macarulla, M., Fuertes, A., Vimont, V., & Pinho, L. M. (2017). A serious game enhancing social tenants' behavioral change towards energy efficiency. In *2017 global internet of things summit (giots)* (pp. 1–6).

Chacon, J. P., Marin, D., & Vidal, M.-I. (2019). Bibliometría aplicada a la gamificacion como estrate-́ gia digital de. *Revista de Educación a Distancia (RED), 19*(60).

Chambers, C., & Tzavella, L. (2020). *The past, present, and future of registered reports*.

Chen, C. (2014). The citespace manual. *College of Computing and Informatics, 1*, 1–84.

Chen, C. (2016). *Citespace: A practical guide for mapping scientific literature*. NY: Nova Science Publishers Hauppauge.

Chen, C., Chen, Y., Horowitz, M., Hou, H., Liu, Z., & Pellegrino, D. (2009). Towards an explanatory and computational theory of scientific discovery. *Journal of Informetrics, 3*(3), 191–209.

Chen, C., Ibekwe-SanJuan, F., & Hou, J. (2010). The structure and dynamics of cocitation clusters: A multiple-perspective cocitation analysis. *Journal of the American Society for Information Science and Technology, 61*(7), 1386–1409.

Chen, C., & Morris, S. (2003). Visualizing evolving networks: Minimum spanning trees versus pathfinder networks. In *IEEE symposium on information visualization 2003 (ieee cat. no. 03th8714)* (pp. 67–74).

Chen, C., Song, I.-Y., Yuan, X., & Zhang, J. (2008). The thematic and citation landscape of data and knowledge engineering (1985–2007). *Data & Knowledge Engineering, 67*(2), 234–259.

Chen, X., & Liu, Y. (2020). Visualization analysis of high-speed railway research based on citespace. *Transport Policy, 85*, 1–17.

Chow, C. Y., Riantiningtyas, R. R., Kanstrup, M. B., Papavasileiou, M., Liem, G. D., & Olsen, A. (2020). Can games change children's eating behaviour? A review of gamification and serious games. *Food Quality and Preference, 80*, Article 103823.

Cosentino, V., Gerard, S., & Cabot, J. (2017). A model-based approach to gamify the learning of modeling. In *Proceedings of the 5th symposium on conceptual modeling education and the 2nd international istar teaching workshop co-located with the 36th international conference on conceptual modeling (ER 2017), Valencia, Spain, November 6-9, 2017* (pp. 15–24).

Dale, G., Joessel, A., Bavelier, D., & Green, C. S. (2020). A new look at the cognitive neuroscience of video game play. *Annals of the New York Academy of Sciences, 1464*(1), 192–203.

Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K., & Harshman, R. (1990). Indexing by latent semantic analysis. *Journal of the American Society for Information Science, 41*(6), 391–407.

Deterding, S. (2012). Gamification: designing for motivation. *Interactions, 19*(4), 14–17.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining" gamification". In *Proceedings of the 15th international academic mindtrek conference: Envisioning future media environments* (pp. 9–15).

Deterding, S., Sicart, M., Nacke, L., O'Hara, K., & Dixon, D. (2011). Gamification. Using gamedesign elements in non-gaming contexts. In *Chi'11 extended abstracts on human factors in computing systems* (pp. 2425–2428).

Dicheva, D., Dichev, C., Irwin, K., Jones, E. J., Cassel, L. B., & Clarke, P. J. (2019). Can game elements make computer science courses more attractive?. In *Proceedings of the 50th ACM technical symposium on computer science education, SIGCSE 2019* (p. 1245).

Djaouti, D., Alvarez, J., & Jessel, J.-P. (2011). Classifying serious games: The g/p/s model. In *Handbook of research on improving learning and motivation through educational games: Multidisciplinary approaches* (pp. 118–136). IGI Global.

Egghe, L. (2006). Theory and practise of the g-index. *Scientometrics, 69*(1), 131–152.

Ferron, M., Loria, E., Marconi, A., & Massa, P. (2019). Play&go, an urban game promoting behaviour change for sustainable mobility. *Interaction Design and Architecture Journal, 40*, 24–25.

Flandoli, A. M. B., & Romero-Riano, E. (2020). El papel de la gamificac ̃on en la conciencia ambi-́ ental: Una revision bibliom ́etrica.: *Revista Prisma Social*, (30), 161–185.

Fleming, T. M., Bavin, L., Stasiak, K., Hermansson-Webb, E., Merry, S. N., Cheek, C., & Hetrick, S. (2017). Serious games and gamification for mental health: Current status and promising directions. *Frontiers in Psychiatry, 7*, 215.

Fogg, B. J. (2002). Persuasive technology: Using computers to change what we think and do. *Ubiquity, 2002*(December), 2.

Foster, E. D., & Deardorff, A. (2017). Open science framework (osf). *Journal of the Medical Library Association: JMLA, 105*(2), 203.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 35–41.

Gaggero, G., Bonassi, A., Dellantonio, S., Pastore, L., Aryadoust, V., & Esposito, G. (2020). A scientometric review of alexithymia: Mapping thematic and disciplinary shifts in half a century of research. *Frontiers in Psychiatry, 11*, 1405.

Grossek, G., Malita, L., & Sacha, G. M. (2020). Gamification in higher education: A bibliometric approach. *eLearning & Software for Education*, 3.

Hamari, J. (2013). Transforming homo economicus into homo ludens: A field experiment on gamification in a utilitarian peer-to-peer trading service. *Electronic Commerce Research and Applications, 12*(4), 236–245.

Hamari, J. (2017). Do badges increase user activity? A field experiment on the effects of gamification. *Computers in Human Behavior, 71*, 469–478.

Hamari, J., & Koivisto, J. (2013). *Social motivations to use gamification: An empirical study of gamifying exercise*.

Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work?–A literature review of empirical studies on gamification. In *2014 47th Hawaii international conference on system sciences* (pp. 3025–3034).

Hamari, J., & Tuunanen, J. (2014). *Player types: A meta-synthesis*.

Huang, C.-K., Neylon, C., Brookes-Kenworthy, C., Hosking, R., Montgomery, L., Wilson, K., & Ozaygen, A. (2020). Comparison of bibliographic data sources: Implications for the robustness of university rankings. *Quantitative Science Studies, 1*(2), 445–478.

Huotari, K., & Hamari, J. (2012). Defining gamification: a service marketing perspective. In *Proceeding of the 16th international academic mindtrek conference* (pp. 17–22).
Huotari, K., & Hamari, J. (2017). A definition for gamification: Anchoring gamification in the service marketing literature. *Electronic Markets, 27*(1), 21–31.
Johnson, C., McGill, M., Bouchard, D., Bradshaw, M. K., Bucheli, V. A., & Merkle, L. D. (2016). Game development for computer science education. In *Proceedings of the 2016 iticse working group reports* (pp. 23–44).
Johnson, D., Deterding, S., Kuhn, K.-A., Staneva, A., Stoyanov, S., & Hides, L. (2016). Gamification for health and wellbeing: A systematic review of the literature. *Internet Interventions, 6*, 89–106.
Johnson, D., Horton, E., Mulcahy, R., & Foth, M. (2017). Gamification and serious games within the domain of domestic energy consumption: A systematic review. *Renewable and Sustainable Energy Reviews, 73*, 249–264.
Kim, S., Song, K., Lockee, B., & Burton, J. (2018). *Gamification in learning and education: Enjoy learning like gaming*. Springer International Publishing.
Kleinberg, J. (2003). Bursty and hierarchical structure in streams. *Data Mining and Knowledge Discovery, 7*(4), 373–397.
Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management, 45*, 191–210.
Landers, R. N. (2014). Developing a theory of gamified learning: Linking serious games and gamification of learning. *Simulation & Gaming, 45*(6), 752–768.
Landers, R. N., Auer, E. M., Collmus, A. B., & Armstrong, M. B. (2018). Gamification science, its history and future: Definitions and a research agenda. *Simulation & Gaming, 49*(3), 315–337.
Landers, R. N., Bauer, K. N., & Callan, R. C. (2017). Gamification of task performance with leaderboards: A goal setting experiment. *Computers in Human Behavior, 71*, 508–515.
Landers, R. N., & Landers, A. K. (2014). An empirical test of the theory of gamified learning: The effect of leaderboards on time-on-task and academic performance. *Simulation & Gaming, 45*(6), 769–785.
Lee, J. J., & Hammer, J. (2011). Gamification in education: What, how, why bother? *Academic Exchange Quarterly, 15*(2), 2. Retrieved from http://www.gamifyingeducation.org/files/Lee-Hammer-AEQ-201%1.pdf.
Leonard, T. C. (2008). *Richard h. thaler, cass r. sunstein, nudge: Improving decisions about health, wealth, and happiness*. Springer.
Lopez-Belmonte, J., Parra-Gonzalez, M., Segura-Robles, A., & Pozo-Sanchez, S. (2020). Scientific´mapping of gamification in web of science. *European Journal of Investigation in Health, Psychology and Education, 10*(3), 832–847.
Marconi, A., Schiavo, G., Zancanaro, M., Valetto, G., & Pistore, M. (2018). Exploring the world through small green steps: improving sustainable school transportation with a game-based learning interface. In *, 24. Proceedings of the 2018 international conference on advanced visual interfaces, AVI 2018* (pp. 1–24), 9.
Marczewski, A. (2013). *Gamification: A simple introduction*. Andrzej Marczewski.
Marti-Parreno, J., Mendez-Ibanez, E., & Alonso-Arroyo, A. (2016). The use of gamification in education: A bibliometric and text mining analysis. *Journal of Computer Assisted Learning, 32*(6), 663–676.
McGonigal, J. (2011). *Reality is broken: Why games make us better and how they can change the world*. Penguin.
Morschheuser, B., Hamari, J., Koivisto, J., & Maedche, A. (2017). Gamified crowdsourcing: Conceptualization, literature review, and future agenda. *International Journal of Human-Computer Studies, 106*, 26–43.
Morschheuser, B., Hamari, J., Werder, K., & Abe, J. (2017). How to gamify? A method for designing gamification. In *Proceedings of the 50th Hawaii international conference on system sciences 2017*.
Morschheuser, B., Hassan, L., Werder, K., & Hamari, J. (2018). How to design gamification? A method for engineering gamified software. *Information and Software Technology, 95*, 219–237.
Nakajima, T., & Lehdonvirta, V. (2013). Designing motivation using persuasive ambient mirrors. *Personal and Ubiquitous Computing, 17*(1), 107–126.
Paiva, J. C., Leal, J. P., & Queiros, R. (2020). Fostering programming practice through games. *Information, 11*(11), 498.
Pedreira, O., Garcıa, F., Brisaboa, N., & Piattini, M. (2015). Gamification in software engineering a systematic mapping. *Information and Software Technology, 57*, 157–168.
Pranckute, R. (2021). Web of science (wos) and scopus: The titans of bibliographic information in˚ today's academic world. *Publications, 9*(1), 12.
Prochaska, J. O., & DiClemente, C. C. (1983). Stages and processes of self-change of smoking: Toward an integrative model of change. *Journal of Consulting and Clinical Psychology, 51*(3), 390.
Putz, L.-M., & Treiblmaier, H. (2015). *Creating a theory-based research agenda for gamification*.
Rajani, N. B., Mastellos, N., & Filippidis, F. T. (2021). Impact of gamification on the self-efficacy and motivation to quit of smokers: Observational study of two gamified smoking cessation mobile apps. *JMIR Serious Games, 9*(2), Article e27290.
Rao, V. (2013). A framework for evaluating behavior change interventions through gaming. In *International conference on advances in computer entertainment technology* (pp. 368–379).
Reeves, B., & Read, J. L. (2009). *Total engagement: How games and virtual worlds are changing the way people work and businesses compete*. Harvard Business Press.
Reid, G. (2012). Motivation in video games: A literature review. *The Computer Games Journal, 1*(2), 70–81.
Rodrigues, L. F., Costa, C. J., & Oliveira, A. (2016). Gamification: A framework for designing software in e-banking. *Computers in Human Behavior, 62*, 620–634.
Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53–65.
Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology, 25*(1), 54–67.
Ryan, R. M., Rigby, C. S., & Przybylski, A. (2006). The motivational pull of video games: A selfdetermination theory approach. *Motivation and Emotion, 30*(4), 344–360.
Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior, 69*, 371–380.
Sardi, L., Idri, A., & Fernandez-Aleman, J. L. (2017). A systematic review of gamification in e-health. *Journal of Biomedical Informatics, 71*, 31–48.
Schoech, D., Boyas, J. F., Black, B. M., & Elias-Lambert, N. (2013). Gamification for behavior change: Lessons from developing a social, multiuser, web-tablet based prevention game for youths. *Journal of Technology in Human Services, 31*(3), 197–217.
Seaborn, K., & Fels, D. I. (2015). Gamification in theory and action: A survey. *International Journal of Human-Computer Studies, 74*, 14–31.
Segura-Robles, A. (2019). Produccion cient´ıfica sobre gamificacion en educaci´on: Un an´alisis cien-´ciometrico scientific production about gamification in education: A scientometric analysis.˙. *Revista de Educacion*´*, 386*, 113–135.
Su, X., Li, X., & Kang, Y. (2019). A bibliometric analysis of research on intangible cultural heritage using citespace. *SAGE Open, 9*(2), 2158244019840119.
Tekinbas, K. S., & Zimmerman, E. (2003). *Rules of play: Game design fundamentals*. MIT press.
Trinidad, M., Ruiz, M., & Calderon, A. (2021). A bibliometric analysis of gamification research. *IEEE Access, 9*, 46505–46544.
Vassileva, J. (2012). Motivating participation in social computing applications: A user modeling perspective. *User Modeling and User-Adapted Interaction, 22*(1), 177–201.
Vieira, V., Fialho, A., Martinez, V., Brito, J., Brito, L., & Duran, A. (2012). An exploratory study on the use of collaborative riding based on gamification as a support to public transportation. In *2012 Brazilian symposium on collaborative systems* (pp. 84–93).
Weiss, J. (2019). Gamification and scholarly ethical perspectives on industries, a bibliometric analysis. In *Proceedings of the 52nd Hawaii international conference on system sciences*.
Whitson, J. R. (2013). Gaming the quantified self. *Surveillance & Society, 11*(1/2), 163–176.
Wolf, T. (2020). Green gamification: How gamified information presentation affects proenvironmental behavior. In *Gamifin* (pp. 82–91).
Xie, P. (2015). Study of international anticancer research trends via co-word and document cocitation visualization analysis. *Scientometrics, 105*(1), 611–622.
Xu, F., Tian, F., Buhalis, D., Weber, J., & Zhang, H. (2016). Tourists as mobile gamers: Gamification for tourism marketing. *Journal of Travel & Tourism Marketing, 33*(8), 1124–1142.
Yen, B. T., Mulley, C., & Burke, M. (2019). Gamification in transport interventions: Another way to improve travel behavioural change. *Cities, 85*, 140–149.
Zheng, L. (2019). Using mutual information as a cocitation similarity measure. *Scientometrics, 119*(3), 1695–1713.
Zhou, W., Chen, Q., & Meng, S. (2019). Knowledge mapping of credit risk research: Scientometrics analysis using citespace. *Economic research-Ekonomska istrazivanja, 32*(1), 3451–3478.
Zichermann, G., & Cunningham, C. (2011). *Gamification by design: Implementing game mechanics in web and mobile apps*. O`Reilly Media, Inc.