SURVEY ARTICLE

Internet-of-Gamification: A Review of Literature on IoT-enabled Gamification for User Engagement

Ruowei Xiao§, Zhanwei Wu$, and Juho Hamari¶

Faculty of Information Technology and Communication Sciences, Tampere University, Tampere, Finland; §School of Design, Shanghai Jiao Tong University, Shanghai, China

ABSTRACT

Engagement is a common goal pursued by most social and technical systems, because of its widely acknowledged effects on enhancing user acceptance and performance. Previous research has shown that a system’s ability to engage users involves two known aspects: the technology foundation that determines the interactive paths for engaging users and the design methodology that determines the atop user experience to be conveyed through those paths. In recent years, an emerging and promising engagement approach that integrates both an advanced technology stack and novel design methodology, i.e., IoT-enabled Gamification (IoG), has attracted wide interest from both public and private sectors. This article aims to conduct a systematic review to answer some fundamental questions. 75 papers were reviewed under a 3-axis analysis framework of user engagement, the majority of which indicated that IoG is linked to increased engagement in a variety of application domains, stages, and population scales.

1. Introduction

In the last decade, the Internet of Things (IoT) has been well developed from its embryo of industrial application and is now considered as a key impetus for the digitization of our society and economy.1 To this end, the active involvement of people and collective wisdom generated by co-creation and co-innovation have been unprecedentedly emphasized in this progress. Horizon Europe, the largest science and research project in Europe, listed public engagement as one of its core targets.2 According to a Gallup report, employee engagement and customer engagement were considered as the key factors for business success and innovation.3 Furthermore, SmartCitiesWorld has claimed that smart cities would not thrive without the active engagement of citizens.4 User engagement hence becomes one of the common design and development goals shared by many recent IoT-based systems and smart services, where people play a profound, multifaceted role combining data consumer, data contributor, and a provider of intelligence and other potential value Table 1–5.

Meanwhile, gamification is a design approach of enhancing services and systems with affordances for experiences similar to those created by games (Koivisto & Hamari, 2019). By transforming systems and services to afford a gameful experience (Hamari, 2007), gamification presents itself as a de facto approach for increasing user engagement in various application domains such as health, education, governance, marketing, and others (Hanus & Fox, 2015; Hassan & Hamari, 2020; Hofacker et al., 2016). In recent years, a rising trend of integrating smart technologies and gamification has been witnessed in both public and private sectors for the purpose of better user engagement. The term “smart gamification” was coined to describe the technical convergence in a broader sense that also covered a wider range of smart technologies like machine learning, intelligent agent, and such (Uskov & Sekar, 2015). However, in this article, we intend to investigate a more concentrated research scope, namely, “IoT-enabled gamification (IoG).” We argue that this approach is increasingly being combined with smart society and industry development agendas, eventually forming an Internet-like information infrastructure that consists of enormous smart gamification systems/services across a vast range of application domains, e.g., the playful city, somatosensory health/education games, and gamification in industry 4.0.

However, even though a certain number of IoT-enabled gamification applications are present, there is still a scant systematic and comprehensive overview, thus hindering a consistent body of knowledge in this area. Although user engagement can actually manifest itself in various forms and scales, the existing literature barely takes this situation into account. Rather, the topic is investigated in a broad and rough way, without conclusions of designable system factors nor a comprehensive evaluation of efficacy. As a consequence, the value of IoT-enabled gamification systems has not been fully synthesized and conveyed, and pragmatic design guidelines for potential practitioners have not been established.

Therefore, this paper aims to propose a systematic conceptual framework to conclude the existing literature body of IoT-enabled gamification and its applications on user engagement by way of a comprehensive and in-depth literature review, extract reusable methods and knowledge, and further contribute to both theoretical and pragmatic foundations for future research in this area.
Table 1. Bibliometric data.

| Discipline           | Amount | Year | Amount | Publication Type | Amount |
|----------------------|--------|------|--------|------------------|--------|
| Sociology            | 16     | 2020 | 1      | Conference Paper | 51     |
| Psychology           | 6      | 2019 | 17     | Article          | 21     |
| Computer Science     | 50     | 2018 | 15     | Book Chapter     | 3      |
| Information Science  | 44     | 2017 | 18     | Article          | 75     |
| Engineering          | 8      | 2016 | 9      | Article          | 75     |
| Management           | 2      | 2015 | 8      | Article          | 75     |
| Art and Design       | 7      | 2014 | 3      | Article          | 75     |
|                      |        | 2012 | 2      | Article          | 75     |
|                      |        | 2011 | 1      | Article          | 75     |
|                      |        | 2008 | 1      | Article          | 75     |
|                      |        |      |        |                  | 75     |

2. Concepts and analysis framework

2.1. Internet of things

The Internet of Things, or IoT, was first introduced by Kevin Ashton to describe how a new kind of pervasive technology can be created by “adding radio-frequency identification and other sensors to everyday objects” (Ashton, 2009). It is a technical paradigm following Mark Weiser’s vision that: “The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it” (Weiser, 2002). Over time, the term has been specified and redefined in several ways. Some define it as “an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment” (Madakam et al., 2015), while others refer to it as “a system of uniquely identifiable objects (things) and virtual addressability that would create an Internet-like structure for remote locating, sensing, operating, and/or actuating of entities” (Ng & Wakenshaw, 2017). Nevertheless, most believe IoT will pave the road toward an Internet of People (IoP) (Conti et al., 2017) and an Internet of Everything (IoE) (Miraz et al., 2015), further leading to a world where all humans, physical objects, and digital services can be connected and communicate in an intelligent fashion.
IoT is becoming a fundamental construction of modern information infrastructure, the application of which can be widely found in a large amount of commercial and open public services. With the prevalence of low-cost, low-power consumption transducers and transducer-embedded smart devices, we have witnessed the emergence of large-scale Wireless Sensor Networks (WSN) for environment monitoring, all the way to the Personal/Body Area Networks (PAN/BAN) that quantify an individual’s daily life and biometric information. An unprecedented level of data awareness and data accessibility has greatly influenced not only how we perceive the surrounding world but also our decision making and behavior patterns (Conti et al., 2017). The data conglomerate can increase the overall interactivity of smart services by providing highly personalized feedback and contextual awareness in a fine-grained granularity. Compared with contemporary legacy systems, the introduction of IoT was proved able to improve energy efficiency (Moreno et al., 2014), reduce time and resource consumption (Malavade & Akulwar, 2016; TongKe, 2013), hence lowering the overall interaction cost. Furthermore, these rapidly developing automation systems also enhance users’ capabilities and their control over the services. Thus, IoT constitutes a technical affordance for engaging users in smart services.

### 2.2. Gamification

Gamification refers to a design approach of enhancing services and systems with affordances for experiences similar to those created by games (Koivisto & Hamari, 2019). It is considered an effective strategy to engage users in desired behaviors by restructuring tasks and activities to integrate game elements and provide gameful experiences. Research in the fields of health (Cugelman, 2013), education (Al-Azawi et al., 2016), tourism (Xu et al., 2017), business (Hofacker et al., 2016), and many others has shown that gamification can promote healthy behaviors, improve learning performance/motivation, or contribute to brand awareness/loyalty. However, the underlying mechanism of gamification still needs further research. Some have argued that gamification provides an engaging user experience because it can:

1. Transport users into a virtual world or alternate reality by immersive and interactive narratives where a desired attitude or behavior can be gained more easily (Burrows & Blanton, 2016). A broader projection mechanism can be found in gamified applications, e.g., storification,
avatars, role playing, or the personification of inanimate objects and content, etc.

(2) Provide incentives to better motivate desired behavior (Banfield & Wilkerson, 2014; Burrows & Blanton, 2016). According to self-determination theory (Deci & Ryan, 2012), people can be motivated by either extrinsic or intrinsic incentives. While the former derives from external sources, e.g., monetary or material rewards, gamification is more frequently associated with the latter. Examples include badges, trophies, levels, and derived social acknowledgment, which originate from the game mechanics and the system itself.

(3) Absorb users into a flow state during an activity, so that they are more willing to adhere to that activity (Constantinescu et al., 2017; Hamari & Koivisto, 2014). A flow state is defined by Mihály Csíkszentmihályi (Csíkszentmihályi & Csikszentmihaly, 1990) as a positive mental state in which a person is fully immersed in a feeling of energized focus, full involvement, and enjoyment in the process of the activity. It is usually triggered by a good balance between perceived challenges and skills.

(4) Enhance users’ performance by correctly setting goals, subgoals, and difficulties (Hamari, 2017; Landers et al., 2017). Goal setting (Locke & Latham, 2013) is a motivation theory explaining the causes of people’s performance in tasks and also recognized as an effective strategy of enhancing self-efficacy (Zimmerman et al., 1992).

### 2.3. IoT-enabled Gamification (IeG)

The earliest attempts to combine IoT and game elements for non-entertainment purposes date back to the 1980s. For example, Honig et al. proposed a rehabilitation system that utilized pressure sensors and television games in 1985 (Honig & Eikelboom, 1985). However, it was during the recent decade that IeG applications have undergone a booming growth, fueled by the unprecedented prevalence of transducer-embedded smart devices and pervasive computing technology. Aside from health, IeG has also been widely adopted in the fields of education, crowdsourcing, smart cities, etc.

The convergence of IoT and gamification is expected to generate more dynamic outcomes for user engagement, interacting with each other in such a way as to offer multiple new benefits, thereby exceeding the sum of their parts. IoT-enabled gamification brings about some synergistic benefits for smart services, for instance, better interactivity leveraging both context awareness and a well-designed gamified mechanism, longer retention of user interest resulting from multisensory feedback and intrinsic motivation, and a lower technical threshold for engaging non-tech-savvy people in a cost-efficient, enjoyable way. None of these can be achieved by exclusively relying on IoT or gamification. Although it is widely believed that IeG can bring about new approaches for smarter and more appealing services, the existing research is scattered across many different application domains, and so, empirical evidence needs to be collected and synthesized through comprehensive literature research in order to guide future practice.

### 2.4. User Engagement (UE)

Despite its wide usage, the term “user engagement” lacks a consensus definition. There are various definitions proposed in different domains. In computer and information science research, engagement is usually defined as whatever compels people to become engaged and sustain their use of a technical system, for example, “a category of user experience characterized..."
by attributes of challenge, positive affect, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control” (O’Brien, 2016). In business and service research, engagement is more recognized as an end goal, while user experience is the means to that end. As an example, Brodie defines it as “A psychological state that appears from an important thing (e.g., a brand) due to interactional experiences and creative participation” (Brodie et al., 2011), while other researchers argue that this psychological state involves both attentional (Westgate & Wilson, 2018), attitudinal (Forbes, 2010) and motivational (Van Doorn et al., 2010) factors. In the education field, engagement is defined as a meta-construct that consists of three sub-constructs: cognitive, emotional, and behavioral engagement (Christenson et al., 2012). As a final example, the public governance domain considers engagement as “actions” that “citizens take in order to pursue common concerns and address problems in the communities they belong to” (Zukin et al., 2006).

The varied definitions above reflect the rather complicated and multifaceted nature of user engagement, which likely contributes to the persistent ambiguity surrounding the term. For example, Doherty and Doherty (2018) found, “though engagement is a major theme of research within HCI and related fields, . . . 65% of publications that address engagement do not provide a definition.” Similarly, in the gamification field, varying definitions of engagement that scrutinize the concept from different perspectives have been adopted in the literature. Take a few review papers as examples, in (Darejeh & Salim, 2016) “engagement” depicted a series of behavior of using software, while in another review, the term was more about motivating people (Gupta & Gomathi, 2017). Looyestyn et al. (2017) used “once off” and “sustained” and Stepanovic et al. used (Stepanovic & Mettler, 2018) “long-term” to distinguish the engagement duration. On the other hand, Blok et al. (2021) and Hassan and Hamari (2020) used “family engagement” and “civic engagement” respectively to describe scale feature and social patterns of the engagement. We argue that it actually reflects a community-wide consensus on the multi-construct nature of engagement, as suggested by O’Brien (2016) and O’Brien and Toms (2008), and the literature body encompasses multi-faceted analysis and report, in return, contributes to a more convergent, fine-grained knowledge base. Hence, we argue that an analytical framework need to be constructed to guide our review process, which is supposed to, first, better communicate different aspects and components of engagement construct to the audience and second, reflect the emerging consensus of research community by learning from previous studies in multidisciplinary fields, including but not confined to gamification, cognitive/behavioral psychology (Kappelman & McLean, 1994), sociology (Marino & Presti, 2019), economy, and marketing (Ng et al., 2020). As a result, the following review framework that consists of three respective axes (as shown in Figure 1) was proposed and used in this study:

Cognitive-Behavior Outcome Axis: To evaluate the underlying psychological mechanism of user engagement more precisely, this axis describes the cognitive-behavioral outcome generated by user engagement: (1) atten
dional engagement refers to raising awareness of a certain subject, or drawing users’ attention toward it (Schmidt et al., 2016); (2) attitudinal engagement refers to shaping/altering users’ attitudes toward the subject (Heide et al., 2012); (3) motivational engagement refers to incentivizing users’ certain behaviors (Martin, 2012); and (4) behavioral engagement refers to the actual practice of or involvement in the desired behavior. It is worth noting that the correlation among attentional, attitudinal, motivational, and behavioral engagement is well-recognized in previous research (Li & Lerner, 2013) and manifested as a psychological continuum (da Rocha Seixas et al., 2016). Hence, it is plausible to treat the Cognitive-Behavior Axis as a consistent, progressive process rather than being anchored at one single phase. Engagement may be initialized at the point when a user’s attention is captured, while the progress will be intensified as the user’s attitude and/or motivation is affected, thus ultimately resulting in his/her behavior change. Therefore, in this research, we intentionally use a continuous interval of cognitive-behavioral phases, e.g., attention and behavior, to better analyze and describe the diverse and dynamic patterns of cognitive-behavioral transition induced by user engagement.

Engagement Stage Axis: According to O’Brien and Toms (2008), user engagement emerged as a process that consists of several different stages “with distinguishable attributes inherent at each stage.” The 2nd axis indicates these stages, with the origin of coordinates starting from non-engagement. The process of

---

Figure 1. 3-axis user engagement construct.
user engagement initializes when users get involved in the target experience for the first time, i.e., the entry point of engagement. As the process continues and the users do not drop out from the current state, it will extend to the stage of sustained engagement, which usually takes place in non-transient, sequential behaviors that consist of more than one atomic action. While the long-term engagement reflects a stable retention of engagement willingness in the long run, it may notably consist of multiple dynamic cycles of engage–disengage–re-engage behaviors. Moving along the positive direction of the axis, we can observe an increasing engagement intensity, while in the opposite direction from engagement to non-engagement, it instead defines the process known as “disengagement.” Disengagement takes place when the users’ interest and motivation are not persistently maintained. Also, if users feel that their goal has been achieved or their needs are fulfilled, it is also likely they will break away from the engagement status.

Engagement Scale Axis: Existing studies also suggest that user engagement can be characterized by the user scale that is required to obtain the desired engagement outcomes (Marino & Presti, 2019; Zukin et al., 2006). (1) Individual Engagement: Although a massive number of users can be present in the same scenario simultaneously, individual engagement behavior can be achieved by engaging a single user. To simply illustrate, a mobile game application is designed for reminding players to take care of their house plants but also provides some social interaction features like social network sharing or a leaderboard. However, the target behavior of house plant care itself can be achieved by individual engagement either with or without interacting with other users. (2) Multi-user engagement: Differing from individual engagement, multi-user engagement usually requires more than one participant and/or stakeholder to be engaged in order to achieve collective goals or group behavior, which may range from family-level to community-level engagement. Examples include a reward posting platform that is shared among family members for learning and using home automation, or a behavior-monitoring digital signage system to increase the hand hygiene compliance of medical staff in ICU. 3) Public engagement: Multi-user engagement can further scale up to a crowd/public level, targeting unspecified user groups or the general public. Most crowdsourcing platforms are typical examples of public engagement, as well as a myriad of smart services that are intended to promote positive transitions in public behaviors related to health, transportation, sustainability, etc.

The 3-axis construct is a conclusive and combined result of previous user engagement research. The three axes were selected as they appeared to be the most commonly shared characteristics among existing literature. Therefore, the construct will constitute a significant part of our coding system for thematic analysis, serving as an important framework and index for answering our research questions, which will be introduced in more detail in the following section.

3. Research methodology

3.1. Research questions

This article aims to answer some practical questions around “how to utilize IeG to design and develop engaging smart services and systems” by systematically synthesizing and analyzing evidence from current state-of-the-art research. Figure 2 presents our research questions and how they are organized around some key research subjects.

RQ1. Is IeG an effective approach to achieve UE?

- RQ 1.1 What UE outcomes are reported in existing research?
- RQ 1.2 How do IoT and Gamification elements interplay in current IeG applications?
- RQ 1.3 What empirical evidence is provided in existing research to verify IeG’s impacts on UE?
- RQ 1.4 Is there any empirical evidence that IeG is more effective than a traditional approach?

RQ2. If IeG is proved to be effective, what key factors of an IeG system (SF), e.g., usability, accessibility, etc., determine its UE outcome?

- RQ 2.1 What SFs are reported in existing research?
- RQ 2.2 Is there any correlation between a specific SF and certain UE outcomes that can be implied from current literature, e.g., better accessibility results in a larger engagement scale?

RQ3. Are different dimensions of the proposed UE construct interdependent?
3.2. Review process

A systematic literature review was conducted, based on the Scopus database. We adopted Scopus because it indexes all other potentially relevant databases, e.g., ACM, IEEE, Springer, etc. Since all of these independent databases rely on platform-specific search algorithms and functions, we solidified our search results to be replicable, rigorous, and transparent by focusing on single search engine results. Our search query string was as follows:

(TITLE-ABS-KEY (gamif*) OR TITLE-ABS-KEY ("pervasive game") OR TITLE-ABS-KEY ("serious game") OR TITLE-ABS-KEY (games-with-a-purpose) OR TITLE-ABS-KEY ("smart game") AND TITLE-ABS-KEY (iot) OR TITLE-ABS-KEY (internet-of-things) OR TITLE-ABS-KEY ("internet of things") OR TITLE-ABS-KEY ("smart city") OR TITLE-ABS-KEY (smart cities) OR TITLE-ABS-KEY (sensor/actuator) OR TITLE-ABS-KEY (sensor/actuator) AND LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch")

The search results were restricted to the categories of (1) conference papers, (2) journal articles, and (3) book chapters, as these categories are able to provide relatively adequate contents for detailed analysis.

Using the aforementioned search string, we acquired a result of 251 hits by the time of October 2020. The authors conducted the first round of screening based on the title and abstract. As a consequence of agreement, 61 results were excluded due to a lack of a clear or significant relationship with IoT and/or gamification; 2 results were identified as misfits, 1 for non-English paper, and 1 for duplication. In addition, there were 7 papers without full-text access. In total, 163 papers remained for the full-content screening.

In the second-round screening, we identified 51 papers as being irrelevant to the topic, 20 as duplication, and 5 papers as literature reviews and surveys. 14 were identified as unqualified papers, which lacked an analyzable description of the research content, approach, and/or result.

In order to avoid omissions as much as possible, we also checked 20 review papers identified in both first and second round screening. 8 papers were excluded due to a lack of relevant review object, for instance, a review on sensing technology and hardware used in gamified systems. 522 references from the remaining 12 reviews were checked then: 91 were neither conference/journal papers nor book chapters, 26 were review or survey papers, 359 were irrelevant to the topic, 28 were duplications, 11 were unqualified for further analysis, 2 were non-English papers, and 2 were without full-text access. As a result, 2 papers were newly added to the review pool.

Finally, we accepted 75 papers and coded them according to the following seven metrics, among which, numbers 3, 4 and 5 allowed multiple tagging:

(1) Bibliometric data: disciplines, publication year, publication type.

Research types: empirical study, research-in-progress, conceptual design. The categorization was based, respectively, on whether a study had both implementation and an analyzable full evaluation, a partial result and on-going progress, or only a conceptual design.

Application domains: health care/wellbeing, sustainability, transportation, economics, energy, education, tourism, industry, smart home/home automation, smart building, entertainment, crowdsourcing, skill training, general purpose.

Engagement scales: individual engagement, multi-user engagement, public engagement.

Engagement stage: entry point of engagement, sustained engagement, long-term engagement, non-engagement.

Cognitive-behavioral outcome: the values were in the form of [x,y], where both x and y came from the set of attention, attitude, motivation, and behavior.

To promote reliability, coding was done by two authors independently, and discrepancies were addressed by discussions between both coders to reach a 100% consensus on the final coding. Centered on our research questions, we further examined the statistical distribution of each metric and investigated the concurrency between some of the metrics, e.g., application domains and different dimensions of user engagement. Aside from the thematic analysis, the authors also carried out in-depth content analysis based on the 75 empirical research sources appearing in the 75 accepted papers. Specific emphasis was also paid to comparatively analyzing the differences between IeG and traditional gamification approaches regarding aspects like application domains, used system factors, effectiveness, etc. The overall results were gathered into domains of bibliometric information, descriptive and empirical results, respectively.

4. Results

4.1. Bibliometric information

4.1.1. Bibliometric distribution

We gathered information from all the papers pertaining to authors, publication years, publication venues, publication types, and disciplines, and examined the bibliometric data of the 75 papers accepted. Except for the year 2020 (the publications of which had not been fully indexed by the time of the literature search), we can conclude that IeG-related publications were relatively scarce before the year 2015, with the earliest paper dating back to 2008. Regarding the publication type, conference papers accounted for 68.0% (51/75) of the whole literature body, 28.0% of articles (21/75), and 4.0% of book chapters (3/75). These results are consistent with our observation that this is a rising research topic and that most studies appeared to be exploratory and preliminary works.

Regarding discipline distribution, we investigated the publication venues, and categorized them into 1) Sociology, 2) Psychology, 3) Computer Science, 4) Information Science, 5) Engineering (referring to a broader sense of engineering other than CS and IS, e.g., energy, mining, electronic engineering, etc.), 6) Management, and 7) Art and Design, based on self-descriptions of the venues. The results showed that more than half of the publication venues fell into multidisciplinary research fields (42/75, 56%). Computer Science (50/75, 66.7%) followed by Information Science (44/75, 58.7%) accounted for the top two dominating disciplines, respectively. Accordingly, it could be implied that while it is still a technology-driven research area, IoT-enabled gamification
has traversed a wide spectrum from design, social science, and psychology to management and has manifested the versatile dynamics of typical socio-technical systems.

4.1.2. Typological metrics
Among the 75 accepted papers, 36 papers (48.0%) were identified as empirical research that presented quantified results of in-depth investigations on the effects that different IoG system factors have on user engagement. 29 papers (38.7%) were identified as research in progress, with either no evaluation or only partial evaluation irrelevant to user engagement. The remaining 10 papers (13.3%) were identified as conceptual design work without any actual implementation and evaluation.

4.1.3. Application domains
From the figure above, it can be concluded that the majority of current IoG applications fell into a few specific domains of health care/wellbeing (29.3%, 22/75), sustainability (28.0%, 21/75), and education (20.0%, 15/75), followed by crowdsourcing (9.3%, 7/75), skill training (8.0%, 6/75) and smart home/home automation (8.0%, 6/75). According to a previous literature review (TongKe, 2013), the top six application domains of traditional gamification were education/learning (42.2%), health/exercise (11.8%), software development/design (7.7%), crowdsourcing (6.9%), business/management (6.2%), and ecological/environment behavior (3.9%), respectively. To better compare both results, we merged “education” with “skill training” corresponding to “education/learning,” and mapped “sustainability” to “ecological/environment behavior.” The results showed that education was the predominant target area of traditional gamification, whereas IoG had a more balanced distribution among different application domains. Specifically, sustainability had a much higher proportion in IoG applications than in traditional gamification. The reason for this might be that IoT has already been widely adopted by energy consumption, environment monitoring, and other sustainability-related fields as a technical infrastructure, thus generating a natural bonding with the gamified applications within this domain. Our empirical research analysis in the next section also supports this insight.

Aside from statistical distribution, the authors also scrutinized whether any correlation existed between different axes of engagement outcomes and certain application domains. The data showed that in the application domains of health care/wellbeing, crowdsourcing, skill training, smart home/home automation, and tourism, 100% of the research tagged related to the final behavior outcome. This was consistent with the reasonable assumption that an actual action is specifically expected in these application domains, instead of stopping with just a change in attitude or awareness. In contrast, the education domain manifested a more even distribution among all four cognitive-behavioral outcomes, probably due to the particularity of education and its width of focus. Similarly, sustainability was also relatively evenly distributed, with a slight inclination toward the behavior outcome, as shown in Figure 3 (Left).

Regarding different engagement scales, a common tendency was seen among the top three application domains of health care/wellbeing, sustainability, and education that over 50% of the research was identified as being related to multi-user engagement, followed by individual engagement at around 40% and the last 10% as public engagement. According to the detailed content analysis, this was because most of the research in these areas involved multiple stakeholders, for instance, therapists and patients, municipal administrators and citizens, teachers and students, etc. The crowdsourcing domain predictably reported the highest percentage of public engagement (57.1%). Since crowd wisdom and the collective knowledge generated by co-innovation progress have been more and more valued at a societal level, the need for a larger scale of citizen participation in all kinds of smart public services can be expected. Accordingly, this will be where future IoGs is likely to find its way toward a wider innovation space.

Last but not least, 100% of the research in the health care/wellbeing domain turned out to incorporate the sustained engagement stage, while entry point of engagement and long-term engagement accounted for a relatively lower percentage of 22.7% and 31.8%, respectively. According to our content analysis, we believe that this was mainly because most research in the health area aimed at engaging patients in treatment, rehabilitation, or physical exercise. Thus, the corresponding IoG design was focused primarily on each standardized, sustained behavioral session, then a repetitive, long-term engagement. On the other hand, crowdsourcing also possessed an identical consistency of 100% with sustained engagement; however, it manifested a different pattern of a second-highest consistency of 71.4% with the entry point of engagement and the lowest consistency of 28.6% with the long-term engagement. This could imply that instead of a long-term, stable retention of user engagement, this domain looks to drag users’ attentions firstly and more critically to

![Figure 3. Application domain – engagement outcome correlation.](image-url)
maintaining their active involvement during a single behavioral session. Generally, the correlation between the application domain and engagement stage was greatly dependent on domain-specific features, and the sustained engagement appeared to be the most involved stage among all domains.

4.2. Descriptive results

4.2.1. What UE outcomes are reported in existing research? (RQ1.1)
In current literature, the reported UE information covers 1) cognitive and behavioral outcomes, 2) the procedural stage of UE, and 3) the population scale of UE.

(1) Cognitive-Behavioral Outcome
The cognitive-behavioral outcomes in the current literature were observed, measured, and described in the literature using a variety of different methods, e.g., by direct observation, system log, self-report questionnaire, etc. In consideration of analysis validity, we adopted an evidence-based method by extracting related keywords, e.g., “behavior,” “interest,” “motivation” etc., and self-claimed statements from the descriptions of research methods and system mechanisms.

If we look at the consistent cognitive-behavioral span instead of the single psychological state, the results showed that nearly half of the papers (49.3%, 37/75) anchored in the interval from Attention to Behavior, and 41.3% (31/75) anchored in the interval from Motivation to Behavior. Attention, Attitude), and Attitude, Behavior) had r3 and 4 papers, respectively, in each interval. It can therefore be implied that the psychological outcome of UE is commonly perceived as a coherent progress that traverses multiple states from attentional to behavioral engagement. Particularly, behavioral engagement was reported most frequently in current literature, possibly because behavior change is relatively easier to observe and measure, and is usually the most desirable outcome.

(1) Engagement Stage
The engagement stage information was collected and analyzed from the assertive claims and direct evidence presented in each paper. Sustained engagement was the most mentioned stage (69/75, 92.0%), followed by entry point of engagement (39/75, 52.0%) and long-term engagement (35/75, 46.7%). 66.7% (50/75) of the overall literature involved more than one stage. However, we also noticed that there was only a very limited amount of research (6.7%, 5/75) that mentioned non-engagement. This may be possibly due to the publication bias that researchers tend to focus on the positive effects of user engagement and results, which are seemingly more statistically significant, interesting, or valuable, rather than those that are negative or less so. This observation suggests that issues related to disengagement such as what parts of the approaches lead to an abandonment of the application still remain unexplored space in the field.

(1) Engagement Scale
The engagement scale information (as shown in Table 6) was extracted from the engagement mechanism and relative system design presented in each paper. The multi-user engagement scale accounted for the largest percentage of reviewed papers (58.7%, 44/75), followed by individual engagement (37.3%, 28/75) and public engagement (12.0%, 9/75). 6 papers (Butgereit & Martinus, 2016; Hwang et al., 2012; Mann et al., 2019; Miraz et al., 2015; Oliveri et al., 2019; Van Der Helm, 2008) were considered to involve both individual and multi-user engagement.

4.2.2. How do IoT and Gamification elements interplay in current IeG applications? (RQ1.2)
Current literature shows that traditional gamification approaches, e.g., badges, leaderboards, etc., were reused in IeG application contexts. However, some unique approaches pertaining to IeG were also discovered, and we have particularly delved into how different IoT and gamification elements interplay in forming these new engagement mechanics and dynamics. The identified IeG-specific approaches include:

Gamification of daily things/everything: Traditional gamification is often devised and developed as either PC/mobile applications or in completely non-digitalized forms such as board games. While IoT has endowed daily objects with the ability to interact with people, IeG further extends these “smart things” into “gamified things” by integrating gamification design. With

| Table 6. Engagement scale. |
|-----------------------------|
| Engagement Scale | Amount | Reference |
|-------------------|--------|-----------|
| Individual Engagement | 28 | (Amaro & Oliveira, 2019; Bahadoor & Hosein, 2016; Ben-Moussa et al., 2017; Butgereit & Martinus, 2016; Diego et al., 2018; Ding et al., 2014; Fernandes et al., 2020; Fischöder et al., 2018; Gawley et al., 2016; Hong & Cho, 2018; Hwang et al., 2012; Innocent, 2016; Konstantinidis et al., 2014; Lu, 2018; Mann et al., 2019; Massoud et al., 2019; Oliveri et al., 2019; Önnapu, 2015; Pargman et al., 2017; Penders et al., 2018; Pokric et al., 2015; Quintas et al., 2016; Rock Zou et al., 2015; Spyrou et al., 2018; Van Der Helm, 2008; Wang & Hu, 2017; Wilkowski et al., 2015; Williams et al., 2019). |
| Multi-user Engagement | 44 | (Agyeman & Al-Mahmood, 2019; Ahuja & Khosla, 2019; Alexandre et al., 2019; Ardito et al., 2018; Briones et al., 2018; Butgereit & Martinus, 2016; Cavano et al., 2017; Casals et al., 2017; Chernier et al., 2019; Dange et al., 2016; Dessureault, 2019; Fahquist et al., 2011; Ferreira & Martins, 2016; Fraterman et al., 2017; Gabrielli et al., 2014; Garcia et al., 2017; Garcia-Garcia et al., 2016; Henry et al., 2018; Hwang et al., 2012; Karime et al., 2012; Kimura & Nakajima, 2019; Kobeissi et al., 2017; Konstantinidis et al., 2014; Koutsouris et al., 2017; L’Heureux et al., 2017; Laine & Sedano, 2015; Lapão et al., 2016; Madar et al., 2014; Mann et al., 2019; Miglino et al., 2014; Monge & Postolache, 2018; Mylonas et al., 2019; Oliver et al., 2018; Oliveri et al., 2019; Palakvangsa-Na-Ayudhya et al., 2017; Papaloannou et al., 2018; Postolache et al., 2019; Radeta et al., 2019; Rowland, 2015; Song et al., 2016; Spyrou et al., 2018; Tziortzioti et al., 2018; Van Der Helm, 2008; Winnicka et al., 2019). |
| Public Engagement | 9 | (Büsching et al., 2016; Chen et al., 2017; Kazhamiakin et al., 2016; Kihara et al., 2019; Krommyda et al., 2018; Poslad et al., 2015; Pouryazdan et al., 2017; Pozzi & Sgardeis, 2016; Tan & Varghese, 2016). |
IoT’s evolution toward an “Internet of People” (Morschheuser et al., 2017) and an “Internet of Everything” (Miraz et al., 2015) where objects, people, and smart services are widely connected, a similar trend for ieG to evolve into a “Gamification of Everything” has also been witnessed in recent literature. Aside from traditional domains like education, health, etc., more extensive and fine-grained gamification application areas have also emerged in both public and private sectors, such as crowdsensing, industry 4.0, smart home/office/cities, and more. As a gamification of everything will provide smarter, more pervasive, and interactive methods for shaping people’s behaviors in their daily life, it hence increases the accessibility of ieG systems, thus enhancing the channel for engaging users in a more profound and context-aware way.

**Embodied experience enhancement:** The combination of IoT and gamification also generates new possibilities for user experience augmentation and innovative gameful design. By leveraging various sensors and actuators, ieG is able to provide multisensory, intuitive interactions in a real-time manner. Exemplary usages identified in the current literature include (1) employing physical-movement-based control by detecting gesture, posture, position, and so on (Lapão et al., 2016; Postolache et al., 2019; Wilkowska et al., 2015); (2) providing multisensory stimulus as informative feedback, including but not limited to vibration, thermal sensation, smell, etc. (Karime et al., 2012; Oliver et al., 2018); (3) coupling (1) and (2) with a simulated environment such as extended reality, to create an immersive user experience (Ben-Moussa et al., 2017). Previous studies showed that embodied enhancement can significantly increase overall system interactivity and is often associated with somatosensory appeal and immersion, both of which are considered to be able to generate positive impacts on user engagement.

**Dynamic User-adapted Incentives:** As previously concluded, one major strategy of traditional gamification is to strengthen users’ intrinsic motivation via game-like mechanics and dynamics such as leaderboards, challenges, levels, etc. However, current psychological research also points out that there are no “one-size-fits-all” solutions for this strategy to obtain optimal effect and that engagement results may vary greatly from individual to individual. For instance, the flow theory suggests that when a task is too easy or too difficult, it will result in users’ quickly dropping-out from the current activity. It can thus be implied that designing a static, general challenge or task may not be enough to engage users with diverse abilities and perceptions, which is indeed often the case. To this end, one of the greatest reinforcements that distinguishes ieG from traditional gamification is that ieG is able to make use of a wide range of contextual information and user behavior data to adjust gamified contents according to each user’s condition and preferences in a dynamic, self-adaptive way. Thus, highly personalized and precise incentivization can be achieved. Exemplary usages include (1) deciding rewards and penalties according to a certain user behavior pattern is recognized (Briones et al., 2018; Dange et al., 2016; Rock Zou et al., 2015), (2) adjust gamification mechanics and dynamics, e.g., difficulty, rules, challenges, etc., according to the data of interest, e.g., the user’s real-time performance (Kazhamiakin et al., 2016; Oliver et al., 2018), and (3) to project physical reality into virtual representation, e.g., avatars or personified characters, for creating emotional appeal and/or a sense of relatedness (Hwang et al., 2012; Lu, 2018; Papaioannou et al., 2018). Compared with traditional gamification, ieG can better prevent users from disengaging from the target behavior, and thus sustained engagement can be expected.

### 4.2.3. What System Factors (SF) are reported in existing research? (RQ 2.1)

From current ieG systems and applications, 10 system factors have emerged that manifested a possible correlation with UE outcomes. According to the mechanism or path that each factor takes effect, we further divided the 10 SFs into three categories. (1) **Perceived enablement**, referring to the SFs that allow users to perceive the improvement in their ability to access, understand, and interact with the system. **Accessibility** and interactability were the two most prominent SFs in this genre. (2) **Perceived appeal**, referring to the SFs that either appeal to users’ sensations via visual, auditory, tactile, olfactory stimulus, etc., or appeal to users’ emotions like pleasure, empathy, and curiosity. Compared with esthetic and novelty appeals, embodied and immersive appeals were found to be relatively more in favor within the ieG research community, probably because these two SFs were more directly associated with IoT’s technical affordance. (3) **Perceived incentive**, referring to heterologous motivations that lead users toward desired behaviors. According to the sources that the different incentives derive from, intrinsic incentives, extrinsic incentives, and social incentives can be seen.

As shown in Table 7, the statistical distribution showed that “Intrinsic incentive” and “Interactability” were ranked as the top two popular SFs in the current literature (85.3%, 64/75 and 84.0%, 63/75 respectively). The prevalent utilization of intrinsic incentives is also consistent with what we have observed from traditional gamification studies (Miranda et al., 2015; TongKe, 2013). However, the empirical evidence also suggested that extrinsic incentives have a better engagement outcome on some occasions, specifically when public or massive behavior transition is targeted. Meanwhile, “Interactability” and the prominent SF of “Accessibility” (73.3%, 55/75) both reflect more of IoT’s technical impact on ieG systems. Further discussion about the usage of each factor and their respective effects will be introduced in the next section.

### 4.2.4. Is there any correlation between SF and UE outcomes? (RQ 2.2)

As shown in Figure 4, intrinsic incentive emerged as the most commonly related SF to all engagement outcomes. While the engagement stage and cognitive-behavior outcome showed a similar distribution over 10 SFs, the engagement scale was relatively different. Specifically, public engagement was found to be closely related to extrinsic incentive and accessibility, individual engagement was associated more with interactability, and multi-user engagement showed an equal distribution over four SFs: intrinsic incentive, interactability, accessibility, and social incentive. A reasonable inference is that some SFs may have greater impacts on certain engagement scales. For example,
| Category          | System Factor          | Explanation                                                                                                                                  | Typical Elements                                                                 | Reference                                                                 | Amount |
|------------------|------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|--------------------------------------------------------------------------|--------|
| Perceived        | Accessibility          | Refers to users’ perception of easiness to access certain systems or services                                                                | Technical or non-technical barrier, cost and time consumption                    | (Agaman & Al-Mahmood, 2019; Ahuja & Khosla, 2019; Arditto et al., 2018; Ben-Moussa et al., 2017; Briones et al., 2018; Büsching et al., 2016; Butgereit & Martinus, 2016; Caivano et al., 2017; Casals et al., 2017; Chen et al., 2017; Cherney et al., 2019; Dessureault, 2019; Diego et al., 2018; Ding et al., 2014; Fernandes et al., 2020; Ferreira & Martins, 2018; Fraternali et al., 2017; Gabrielli et al., 2014; Garcia et al., 2017; Gawley et al., 2016; Henry et al., 2018; Hong & Cho, 2018; Hwang et al., 2012; Innocent, 2016; Karime et al., 2012; Kazhamiakin et al., 2016; Kimura & Nakajima, 2019; Koutsouris et al., 2018; Krommyda et al., 2018; Lu, 2018; Madar et al., 2014; Mann et al., 2019; Miglino et al., 2014; Monge & Postolache, 2018; Mylona et al., 2019; Oliver et al., 2018; Oliveri et al., 2019; Ōunapuu, 2015; Palakovanga-Na-Ayudhya et al., 2017; Papaioannou et al., 2018; Penders et al., 2018; Pokric et al., 2015; Poslad et al., 2015; Postolache et al., 2019; Pouryazdan et al., 2017; Pozzi & Sgardellis, 2016; Quintas et al., 2016; Rock Zou et al., 2015; Rowland, 2015; Song et al., 2016; Spyrou et al., 2018; Spyrou et al., 2018; Tan & Varghese, 2016; Tzirtzioti et al., 2018; Wang & Hu, 2017) | 55     |
|                  | Comprehensiveness      | Refers to how well the users are informed about the system and services.                                                                       | System helper, information assistant                                              | (Ahuja & Khosla, 2019; Amaro & Oliveira, 2019; Casals et al., 2017; Cherney et al., 2019; Fahlquist et al., 2011; Fischöder et al., 2018; Fraternali et al., 2017; Innocent, 2016; Kihara et al., 2019; Laine & Sedano, 2015; Miglino et al., 2014; Monge & Postolache, 2018; Mylona et al., 2019; Oliver et al., 2019; Ōunapuu, 2015; Palakovanga-Na-Ayudhya et al., 2017; Papaioannou et al., 2018; Pokric et al., 2015; Rock Zou et al., 2015; Rowland, 2015; Spyrou et al., 2018; Spyrou et al., 2018; Tzirtzioti et al., 2018; Wang & Hu, 2017; Williams et al., 2019) | 25     |
|                  | Interactability        | Refers to a broader range of interactive mechanisms that determine the degree and methods of information exchanged between systems and users | Feedback, control flow, contextual awareness                                     | (Agaman & Al-Mahmood, 2019; Ahuja & Khosla, 2019; Alexandre et al., 2019; Amaro & Oliveira, 2019; Arditto et al., 2018; Bahadoor & Hosein, 2016; Ben-Moussa et al., 2017; Butgereit & Martinus, 2016; Casals et al., 2017; Dange et al., 2016; Fahlquist et al., 2011; Fernandes et al., 2020; Fischöder et al., 2018; Fraternali et al., 2017; Gabrielli et al., 2014; Garcia et al., 2017; Garcia-Garcia et al., 2017; Gawley et al., 2016; Henry et al., 2018; Hong & Cho, 2018; Hwang et al., 2012; Innocent, 2016; Karime et al., 2012; Kazhamiakin et al., 2016; Kihara et al., 2019; Kimura & Nakajima, 2019; Kobeissi et al., 2017; Konstantinidis et al., 2014; Koutsouris et al., 2018; Krommyda et al., 2018; L’Heureux et al., 2017; Lapão et al., 2016; Lu, 2018; Madar et al., 2014; Mann et al., 2019; Massoud et al., 2019; Miglino et al., 2014; Monge & Postolache, 2018; Mylona et al., 2019; Oliver et al., 2018; Oliveri et al., 2019; Ōunapuu, 2015; Palakovanga-Na-Ayudhya et al., 2017; Papaioannou et al., 2018; Pargman et al., 2017; Penders et al., 2018; Pokric et al., 2015; Poslad et al., 2015; Postolache et al., 2019; Pozzi & Sgardellis, 2016; Quintas et al., 2016; Radeta et al., 2019; Rock Zou et al., 2015; Rowland, 2015; Song et al., 2016; Spyrou et al., 2018; Spyrou et al., 2018; Tan & Varghese, 2016; Van Der Helm, 2008; Wang & Hu, 2017; Wilkowska et al., 2015; Williams et al., 2019; Winnicka et al., 2019) | 63     |
| Perceived        | Esthetic appeal        | Refers to the design style adopted by a system or service that generates positive aesthetic experience                                          | Graphical interface, music                                                        | (Casals et al., 2017; Fischöder et al., 2018; Garcia-Garcia et al., 2017; Innocent, 2016; Palakovanga-Na-Ayudhya et al., 2017; Pargman et al., 2017; Pokric et al., 2015; Rock Zou et al., 2015; Rowland, 2015; Van Der Helm, 2008) | 10     |
|                  | Embodied appeal        | Refers to the way the interface appeals to or utilizes the user’s sensorimotor system                                                        | Tactile, olfactory, gustatory stimulus; physical movement based control          | (Agaman & Al-Mahmood, 2019; Alexandre et al., 2019; Amaro & Oliveira, 2019; Arditto et al., 2018; Ben-Moussa et al., 2017; Butgereit & Martinus, 2016; Chen et al., 2017; Fischöder et al., 2018; Gabrielli et al., 2014; Gawley et al., 2016; Hong & Cho, 2018; Hwang et al., 2012; Karime et al., 2012; Kihara et al., 2019; Kobeissi et al., 2017; Konstantinidis et al., 2014; Krommyda et al., 2018; Laine & Sedano, 2015; Madar et al., 2014; Miglino et al., 2014; Monge & Postolache, 2018; Oliver et al., 2018; Padnell et al., 2020; Palakovanga-Na-Ayudhya et al., 2017; Pargman et al., 2017; Postolache et al., 2019; Pozzi & Sgardellis, 2016; Radeta et al., 2019; Song et al., 2016; Spyrou et al., 2018; Van Der Helm, 2008; Wang & Hu, 2017; Wilkowska et al., 2015) | 32     |

(Continued)
| Category | System Factor | Explanation | Typical Elements | Reference                                                                 | Amount |
|----------|---------------|-------------|------------------|---------------------------------------------------------------------------|--------|
| Immersive appeal | Refers to user's feeling of being transported to another environment in a metaphorical or immersive way. | Avatar, personification, narrative, role playing | (Alexandre et al., 2019; Ben-Moussa et al., 2017; Casals et al., 2017; Chen et al., 2017; Chen et al., 2017; Chern et al., 2019; Fahlgquist et al., 2011; Fischöder et al., 2018; García-García et al., 2017; Henry et al., 2018; Kihara et al., 2019; Konstantinidis et al., 2014; Krommyda et al., 2018; Lu, 2018; Madar et al., 2014; Oliveri et al., 2019; Öünapuu, 2015; Pargman et al., 2017; Postolache et al., 2014; Rock Zou et al., 2015; Rowland, 2015; Song et al., 2016; Wang & Hu, 2017; Williams et al., 2019) | 23 |
| Novelty appeal | Refers to providing new contents in order to acquire users' sustained curiosity and interests. | Time-limited tasks or challenges, downloaded contents, patches, Leaderboard, competition, collaboration, feeling connected with others | (Ahuja & Khosla, 2019; Amaro & Oliveira, 2019; Innocent, 2016; Kazhamiakin et al., 2016; Poslad et al., 2015; Rowland, 2015) | 6 |
| Perceived Incentive | Social incentive | Refers to the incentives that users can gain from direct or indirect interaction with others. | (Ahuja & Khosla, 2019; Ardito et al., 2018; Bahadoor & Hosein, 2016; Butgereit & Martinus, 2016; Caivano et al., 2017; Casals et al., 2017; Dange et al., 2016; Dessureault, 2019; Diego et al., 2018; Fahlgquist et al., 2011; Ferreira & Martins, 2018; Fraternali et al., 2017; García et al., 2017; García-García et al., 2017; Gawley et al., 2016; Henry et al., 2018; Hwang et al., 2012; Innocent, 2016; Kazhamiakin et al., 2016; Kihara et al., 2019; Kimura & Nakajima, 2019; Kobeissi et al., 2017; L'Heureux et al., 2017; Laine & Sedano, 2015; Lapão et al., 2016; Madar et al., 2014; Mann et al., 2019; Miglino et al., 2014; Mylonas et al., 2019; Oliveri et al., 2019; Palavangsa-Na-Ayudhya et al., 2017; PAPAIOANNOU et al., 2018; Penders et al., 2018; Pokric et al., 2015; Poslad et al., 2015; Quintas et al., 2016; Radeta et al., 2019; Rowland, 2015; Tziortzioti et al., 2018; Van Der Helm, 2008; Wang & Hu, 2017; Winnicka et al., 2019) | 42 |
| Intrinsic incentive | Refers to the incentives that users can gain from the internal mechanism of the systems or services | Badges, goals, challenges, achievements | (Agymen & Al-Mahmood, 2019; Ahuja & Khosla, 2019; Alexandre et al., 2019; Amaro & Oliveira, 2019; Ardito et al., 2018; Bahadoor & Hosein, 2016; Ben-Moussa et al., 2017; Briones et al., 2018; Butgereit & Martinus, 2016; Caivano et al., 2017; Casals et al., 2017; Chen et al., 2017; Dange et al., 2016; Dessureault, 2019; Ding et al., 2014; Fahlgquist et al., 2011; Ferreira & Martins, 2018; Fischöder et al., 2018; Fraternali et al., 2017; Gabrielli et al., 2014; Garcia et al., 2017; Garcia-García et al., 2017; Gawley et al., 2016; Henry et al., 2018; Hwang et al., 2012; Karime et al., 2012; Kazhamiakin et al., 2016; Kihara et al., 2019; Kimura & Nakajima, 2019; Konstantinidis et al., 2014; Koutsouri et al., 2018; Krommyda et al., 2018; L'Heureux et al., 2017; Laine & Sedano, 2015; Lapão et al., 2016; Madar et al., 2014; Mann et al., 2019; Massoud et al., 2019; Miglino et al., 2014; Monge & Postolache, 2018; Mylonas et al., 2019; Oliver et al., 2018; Oliveri et al., 2019; Öünapuu, 2015; Palavangsa-Na-Ayudhya et al., 2017; PAPAIOANNOU et al., 2018; PARGMAN et al., 2017; Penders et al., 2018; Pokric et al., 2015; Poslad et al., 2015; Postolache et al., 2019; POURYAZDAN et al., 2017; Pozzi & Sgardelis, 2016; Quintas et al., 2016; RADETA et al., 2019; Rock Zou et al., 2015; Song et al., 2016; Spyrou et al., 2018; Spyrou et al., 2018; Tan & Varghese, 2016; Tziortzioti et al., 2018; WILKOWSKA et al., 2015; WILLIAMS et al., 2019; Wynnicka et al., 2019) | 64 |
| Extrinsic incentive | Refers to the external incentives that users can gain from outside the mechanism of systems or services. | Monetary reward, in-kind reward, coupons | (Briones et al., 2018; Büsching et al., 2016; Caivano et al., 2017; Diego et al., 2018; Ding et al., 2014; Fernandes et al., 2020; Ferreira & Martins, 2018; Fraternali et al., 2017; García et al., 2017; Palavangsa-Na-Ayudhya et al., 2017; Poslad et al., 2015; POURYAZDAN et al., 2017; Spyrou et al., 2018; Tan & Varghese, 2016) | 14 |

individual engagement predictably involved less social incentive compared with multi-user engagement. Surprisingly, public engagement appeared to involve the least social incentive. After content analysis, we argued that one possible reason may be that the current IoT infrastructure is not yet sufficient to support massive social interaction, specifically with an unspecified majority of people involved. A fully fledged information infrastructure and corresponding socio-technical solutions are prerequisites for supporting large-scale social interaction, among which the Social Internet of Things is considered as one of the promising directions (Atzori et al., 2012). The Social IoT is still under development but has already aroused great interest from large companies, such as Facebook and Google (Rho & Chen, 2018). As technology matures, IoT that can support public engagement may become a new hot area. In this literature review, we identified three papers that have researched
this topic from either theoretical or lower layer technology aspects (Kazhamiakin et al., 2016; Kihara et al., 2019; Poslad et al., 2015).

4.2.5. Are different dimensions of the proposed UE model interdependent? (RQ3)

As shown in Figure 5 (left), research on public engagement showed more interest in attention and attitude than individual and multi-user engagement research. This phenomenon is consistent with the Nudge Theory, which is being actively incorporated by many governments into their public engagement strategies. “Nudge” is a concept suggested by economist Richard Thaler and legal scholar Cass Sunstein (Thaler & Sunstein, 2010), which proposed positive reinforcement and indirect suggestions as ways to influence people’s behavior and decision making. Behavior change on a population level is never an easy task. The nudge theory argued that a more applicable strategy is to draw people’s attention or strengthen their attitude instead of directly regulating their behavior, by better designing and presenting a “choice architecture” (Brown, 2012; Vetter & Kutzner, 2016).

Regarding the correlation between engagement stage and cognitive-behavioral outcome, we noticed that the consistency rate between the entry point of engagement and the [attention, attitude] interval, as well as long-term engagement and [motivation, behavior], both reached an extremely high percentage of 100%. The former is consistent with our preconception that the entry point of engagement and the cognitive stage of human attention are interdependent. While the latter, on the other hand, indicates that all the research involving long-term engagement also involved behavior changes at the same time. However, not all the research targeting behavior changes were aimed at long-term engagement, and this implies a more intensive, but one-way concurrent relation between long-term engagement and the behavioral phase, in contrast to the other engagement stages.

Regarding the correlation between engagement stage and scale, as shown in Figure 5 (Right), sustained engagement appeared to be the most related stage to all three engagement scales (92.9% of individual engagement, 93.2% of multi-user engagement and 88.9% of public engagement respectively). Moreover, public engagement manifested the closest relationship with the entry point of engagement (66.7%), in comparison to individual engagement (50.0%) and multi-user engagement (47.7%).

4.3. Empirical results

Among all the reviewed papers, 36 papers were spotted as empirical studies with full implementation and detailed evaluation results. To further investigate IeG’s efficacy and effectiveness over user engagement, we particularly analyzed the empirical evidence collected from each empirical study, and a detailed analysis can be found in Appendix A. Some preliminary answers to the research questions are provided below.

4.3.1. What empirical evidence is provided to verify IeG’s impacts on UE? (RQ 1.3)

(1) Evidence of improved cognitive-behavioral engagement outcome. 6 papers evaluated attentional engagement, and IeG’s improvement in piloting users’ attentions or awareness toward a system and/or system-encouraged activities was observed. Specifically, 3 papers reported that users’ attentional engagement increased after using IeG systems, and 1 paper reported that the IeG system had better engagement outcome compared with the traditional application. We also noticed that current methods to measure attentional outcomes were mostly manual approaches like self-report questionnaires, psychometric tests, user interviews, and interaction record analysis. Although it is technically feasible to automate the procedure by adopting psycho-physiological measurements like eye-tracking, EEG sensing, etc., this method is still greatly restricted by issues such as cost and accuracy in real practice.

20 papers evaluated attitudinal engagement, with 18 reporting positive effects from different aspects, 1 reported no significant difference, and 1 reported a negative result. Positive results include (1) general positive feedback or welcome attitude after interacting with IeG systems (7 papers); (2) perceived system usefulness, effectiveness, or satisfaction (8 papers); (3) enjoyable or attractive user experience (3 papers); and (4) perceived positive changes in attitudes/opinions (1 paper). The only negative result was reported because the system-encouraged behavior was considered irrelevant or unfeasible. Similar to attentional engagement, the measurement for attitudinal engagement included self-report questionnaires, psychometric tests, and user interviews.
9 papers evaluated motivational engagement. As a result, IeG was reported to be able to increase and/or maintain users' motivation to conduct and/or repeat a target behavior that was encouraged by the system. 1 paper reported that the more times the IeG system was used, the stronger users' motivation grew. Self-report questionnaires, psychometric tests, and expert ratings were utilized to evaluate the motivation engagement outcome.

21 papers evaluated behavioral engagement, among which 20 papers reported positive behavioral outcomes via pre-post comparison or control group experiment, and 1 paper reported no significant changes before and after using the IeG system. Reported effects included performance improvement of existing behavior (13 papers), frequency changes (10 papers), and new behavior/habit forming (4 papers). Target behaviors ranged from work performance and learning to sustainable behavior. A large proportion of the studies leveraged IoT to recognize and monitor human behavior as well as the surrounding environment, hence a system log-based evaluation became the most utilized measurement method (21 papers), followed by self-report questionnaires (19 papers), user interviews (12 papers) and observations (6 papers).

(1) **Evidence of engagement stage applicability.** 22 papers described IeG systems that involved the entry point of engagement applicability, i.e. a successful direction of users' attentions toward the use of system and/or system-encouraged attitude/behavior. 36 papers described sustained engagement applicability, i.e. completion of an uninterrupted operation that requires continuous use of the system. 26 papers described long-term engagement applicability, i.e. the repetitive use of the system and/or long-term retention of system-encouraged attitude/behavior. In addition, 5 papers involved non-engagement, i.e. drop-out from using the system, neglect or opposition of system-encouraged attitude/behavior.

(2) **Evidence of engagement scale applicability.** Regarding the engagement scale, 10 papers targeting individual engagement had sample sizes for user experiments ranging from 6 to 504 participants. 28 papers targeting multi-user engagement had sample sizes ranging from 4 to 1,819 participants. 6 papers targeting public engagement had sample sizes from 4 to 15,600 participants. With varying degrees of effectiveness, the IeG approach was reported as applicable to use on a wide range of user scales, as well as diverse social interaction patterns.

### 4.3.2. Is IeG more effective than a traditional approach? (RQ 1.4)

Since IeG is a newly emerging method for user engagement, there is still insufficient comparative analysis that systematically studies the differences between IeG and its parallel approaches. Yet, we managed to plot several papers that compared IeG's user engagement effects with its traditional counterparts, such as general systems without gamification and gamified applications. In Chen et al. (2017)’s user experiment, participants were asked to use both IeG and mobile applications, then give feedback using a Likert scale. The results showed that IeG was considered both more attractive and enjoyable. Lu (2018) compared IeG and non-IoT gamification’s effects on promoting daily energy saving behaviors, and found that the IeG application reduced energy consumption by 37% more than the non-IoT gamified application on average. Miglino et al. (2014) compared three different psycho-pedagogical methods with their respective IeG-enhanced versions, and in the third study, a control group experiment was used. The results showed that while the learning performance of the participants who used the IeG systems manifested no significant difference from those who used the traditional one, most participants agreed that the user experience of the IeG system was more socializing and enjoyable, hence more engaging. In addition, Oliver et al. (2018) conducted an expert evaluation and concluded that the integration of IoT was able to magnify the performance of general gamified telerehabilitation systems.

In general, the effects of IeG-enhanced systems were reported as identical or above their traditional counterparts from different perspectives and application domains.

### 4.3.3. Is there any correlation between a specific SF and certain UE outcomes? (RQ 2.2)

During this review, we identified a limited amount of scattered empirical evidence, indicating that specific SFs are correlated to certain UE outcomes, either directly or indirectly. For example, in Bahadoor’s study (2016), experiment participants reported that social seed (social incentive) and discount rewards (extrinsic incentive) were the two SFs they perceived.
most useful for keeping using the IeG system and retaining safe driving behaviors such as obeying speed limits, stable driving without sudden lane changes or speed-up/down, etc. (long-term engagement). Alexandre et al. (2019) used a control group experiment and pre-post comparison and found that imparting security and privacy-related knowledge (comprehensiveness) helped raise smart watch users’ awareness of privacy protection. However, the authors also pointed out that although some users understood how to protect their privacy and admitted the importance of this issue, they consciously chose to ignore it due to inconvenience (accessibility) and other reasons. This showed that comprehensiveness, i.e., users’ understanding about the system and/or system-promoted behavior, can contribute to the cognitive outcome at awareness and/or attitude levels. However, if the target is behavior change, then it may also require the incorporation of other SFs to overcome the “attitude-behavior gap” (Fazio & Roskos-Ewoldsen, 2005). In (Casals et al., 2017), a smart serious game for promoting energy saving was proposed. Aside from providing users with energy saving tips (comprehensiveness), intrinsic incentives like scores and missions were also used. It was found that players who achieved higher scores and completed more missions in the game turned out to also have better electricity saving results, which implies that intrinsic incentives can act as an important impetus to putting knowledge into practice ([motivation, behavior]). Further research suggested that SFs like social incentives (team-based competition), embodied appeal (physical interaction), interactivity (adaptive contextual awareness), etc., may have a compound impact on behavioral outcome (Hwang et al., 2012; Lu, 2018). To note that, Poslad (Poslad et al., 2015) reported that the use of challenges and rewards has the potential to change users’ behaviors, but they need to be individualized to achieve an optimal outcome, and the effects are usually highly context-dependent. Also, a social network feature was perceived as useful as it supported information sharing and exchanging, however, it did not necessarily contribute to shifting users’ behavior itself. Generally, it can be concluded that even for the same SF, the final UE outcome it generates depends on both what specific form it takes, as well as how it incorporates with other SFs to constitute the overall IeG system mechanics and dynamics.

Many other studies evaluated only the general user experience and usability, without breaking down elaborate system factors. It is also noteworthy that the correlation revealed by some empirical evidence may not necessarily be limited to a causal relationship. For example, simple concurrency or an interrelated relationship was often found in many education and skill training IeG systems, where knowledge impartation often acts as both a system factor for improving UE and the system-encouraged behavior itself. To briefly sum up, it is still too early to make an assertion about the effectiveness of each system factor and their combined effects, until a more solid validation is made. Therefore, more future studies based on rigorous experiments and empirical evidence are needed to generate reliable knowledge for guiding engaging IeG system design and development.

5. Conclusion and discussion

As a brief conclusion, IeG has manifested great potentials as an emerging UE approach, the instantiation of which will be of value for developers and designers across diverse application domains, including but not limited to sustainability, healthcare, education, industry 4.0, smart cities, and public services.

5.1. Limitations

There are a few limitations related to this work. To ensure the reliability of the thematic analysis, structured codes and an inter-coder method were adopted to determine the final coding. However, possible bias may still exist due to the coder subjectivity. Also, to obtain a controllable amount of query results, the authors intentionally specified the query string using explicit expressions of IoT and gamification-related keywords. However, it was inevitable that papers with implicit or domain-specific expressions in their titles and abstracts, e.g., “embodied interaction,” “edutainment,” etc., were excluded from this review.

5.2. Major findings

In this study, 75 papers regarding IeG, among which 36 were identified as empirical research, were analyzed systematically according to the proposed 3-axis UE model, respectively: cognitive-behavioral outcome, engagement stage, and engagement population scale. Our major findings are concluded below.

First, although existing literature has covered most research space defined by the aforementioned three axes, mainstream studies tend to focus on motivational and behavioral engagement, sustained engagement, and multi-user engagement. Empirical evidence showed that well-designed IeG systems can generate significant impacts on user engagement. This finding is allied with previous literature reviews on gamification and engagement in other fields (Darejeh & Salim, 2016; Hassan & Hamari, 2020; Looyestyn et al., 2017). However, most gamification literature reviews discussed “engagement” as a whole or from one exclusive aspect. As an example, Stepanovic et al. argued that “long-term engagement … is too often neglected” (Stepanovic & Mettler, 2018). To this end, this article contributes to the state of the art by explicating current literature body based on a multi-faceted analytical framework. Specifically, the results showed that better behavioral performance, longer retention, and a larger user population can be expected.

Second, as IoT and gamification merged into a new continuum, several novel approaches have emerged, including 1) gamification of daily things/everything, 2) embodied experience enhancement, and 3) dynamic user-adapted incentives. Existing research showed that these hybrid methods presented greater behavior improvement, and they were better accepted by users or considered more effective by domain experts. There was also unique research that conducted control
group experiments or evaluations to comparatively study the differences between IeG and existing solutions. However, more empirical evidence is needed before we can draw a conclusion that the user engagement outcome of IeG has exceeded that of traditional gamification.

Last but not least, 10 IeG system factors have manifested possible correlations with engagement outcome. We further divided these into three categories, namely perceived enablement, perceived appeal, and perceived incentives. Among all, accessibility and interactability in the group of perceived enablement, embodied and immersive appeal in the group of perceived appeal, as well as intrinsic incentive in the group of perceived incentives turned out to be the most accentuated SFs in each group, respectively. Empirical evidence also suggested that certain SF groups have stronger effects on specific engagement outcomes, e.g., perceived incentive was more associated with motivational and behavioral engagement, while perceived appeal was more associated with attentional and attitudinal engagement. A few previous literature studies also investigated specific uses of gamification elements, e.g., reward, goals, and points. However, the results were highly domain/application specific and not necessarily aligned. For example, Looyestyn et al. found that gamification systems for online program engagement favor leaderboard (one of the social incentives) the most (Looyestyn et al., 2017), while Hassan et al. found that gamification systems for civic engagement prefer points (one of the intrinsic incentives) to leaderboards (Hassan & Hamari, 2020). In IoT-enabled gamification systems, the intrinsic incentives were found the most popular SF, which was closer to Hassan et al.’s finding. Similar conclusions can also be drawn by comparing the uses of other gamification elements like avatar, story, goal setting, and challenge, etc (Bloek et al., 2021; Darejeh & Salim, 2016; Gupta & Gomathi, 2017; Hassan & Hamari, 2020; Looyestyn et al., 2017; Stepanovic & Mettler, 2018); however, the detailed discussion was not included in this paper.

5.3. Discussions for future research

As a rising multidisciplinary research field, IeG still has plenty of unexploited areas. To establish a comprehensive theoretical and practical knowledge base, there remain several critical issues to be addressed in future work:

1) Accessibility may become the first bottleneck for IeG. In comparison to IeG applications that involve users at family and community levels, most applications that claimed to target a massive public actually adopted individual-oriented approaches. Consequently, this made the accessibility of each and every target user a prerequisite before any of the engagement factors takes effect. As an undesired result, many non-commercial applications and services, like those mentioned in studies (Poslad et al., 2015; Pozzi & Sgarelidis, 2016), were forced to confront a dilemma: How to make their systems “commercially successful” to gain a large enough user base in the first place? To this end, Gawley et al. (2016) provided an example to balance commercialization and the promotion of target behavior, in which a mobile game based on smart bracelet data was developed to encourage wearers’ daily physical exercise. Interestingly, the game was not only confined to smart bracelet owners but also could be downloaded and played by general mobile users. Disentangling the gamified contents from those system components that may become hurdles and therefore eliminate possible users is an approach that is not only able to extend the accessibility among all of the potential audience but also one that increases the possibility to attract and direct non-target users’ interest toward the desired attitude/behavior that the system promotes. This is particularly true for those IeG systems coupled with smart devices, the hardware availability of which may take priority over any other technical barriers. Büsching et al. (2016) and Tan and Varghese (2016) tried to tackle this problem by distributing low-cost devices (an RFID-embedded key holder) or installing the equipment (a smart cycling machine) in a publicly accessible place. While it may be unrealistic or unaffordable on some occasions to deploy a real physical implementation, simulation using a miniature system (Cherner et al., 2019; Öunapuu, 2015) or in a fully virtualized form (Oliveri et al., 2019; Wang & Hu, 2017) may be a cost-efficient way to enhance public accessibility.

2) Data intensive Gamification. Distinct from traditional gamification, IeG systems are usually accompanied by massive data generated by numerous sensor nodes and smart objects. It entails a sophisticated mechanism to handle and better exploit especially highly sensitive personal data collected from the personal area network (PAN) and body area network (BAN). On one hand, the existing mechanics, dynamics and even aesthetics applied to gamified applications will possibly become driven by the data as presented in the previous discussion of RQ1.2. By further measuring and analyzing users’ instantaneous physical/mental status via biofeedback, it provides factual evidence complementary to self-reported results and helps understand questions like when and what makes users disengage, etc, thus strengthening the validity of engagement studies as a whole. On the other hand, gamification can actually take place in each and every stage in the life cycle of user data, e.g., in data generation which is already familiarized by various crowdsourcing/sensing IeG systems (Chen et al., 2017; Pouryazdan et al., 2017; Pozzi & Sgarelidis, 2016). While data processing has overlaps with data generation, it emphasizes more on manually tagging or categorizing data (Krommyda et al., 2018; L’Heureux et al., 2017), which is not necessarily generated by the users themselves. Data representation in IeG usually refers to extracting useful information from voluminous raw data and representing it in a meaningful and gameful way, for example, in the form of personified data (Oliver et al., 2018; Papaoannou et al., 2018) or data visualization using AR/VR (Pokric et al., 2015). IeG systems involving data management and consumption also widely exist, and an exemplary application is the gamified Building Information Modeling (BIM) system. Rowland (2015) proposed using a Multiuser-Online-Game-like paradigm to maintain BIM data in an open, real-time manner, which is identical to the digital twin of an architecture in a sense. It is noteworthy that like any other data intensive system, IeG is also facing security and privacy issues, however, deeper discussions of this fall outside our research scope in this article.
3) **IoE-mediated Social Game/Gamification.** The interplay between IoT and gamification has also diversified the interaction patterns among users, and some unique trends have emerged from the current literature. Firstly, social robots were found to be utilized in traditional domains like education, where the term “edutainment robot” was coined (Miglino et al., 2014; Spyrou et al., 2018). It can be foreseen that besides humanoid robots, more and more polymorphic robots like drones and such ones will certainly become part of future IoE systems in diverse application scenarios. However, how to provide a “meaningful” experience that is functionally, socially and affectively associated with human users, is a question beyond what IoT can answer alone. Second, embodied interaction based on psychophysiological/behavioral sensing has provided an alternative channel other than traditional verbal interaction. For instance, Mann et al. (2019) proposed a system for multiple players to compete using visualized brainwaves. In Hwang’s study (2012), an exergame used smart exercise machines, e.g., a treadmill, to detect a runner’ speed. A player could collaborate with his/her teammate by adjusting the running pace, and then further compete with other teams. Finally, hybrid social experience will further blur the boundaries between online and offline users (Fahlquist et al., 2011), as well as between virtual and physical reality (Hwang et al., 2012). As social networks have rapidly penetrated people’s daily life, many IoE systems also try to leverage its network effect as an entry for initializing engagement, or as reentry for repetitive engagement. However, as media by which people’s physical, digital and social existences coincide social networks’ potential to deliver a coherent, hybrid user experience has not yet been fully exploited. Moreover, by incorporating social sensing and mining, it is possible to comprehend complicated social context. Together with physical environment data extracted by IoT sensors, more context-aware, target-oriented engagement effects can be expected.

### References

Agyeman, M. O., & Al-Mahmood, A. (2019, June). Design and implementation of a wearable device for motivating patients with upper and/or lower limb disability via gaming and home rehabilitation. In 2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC) (pp. 247–252). IEEE.

Ahuja, K., & Khosla, A. (2019). Data analytics criteria of IoT enabled smart energy meters (SEMs) in smart cities. International Journal of Energy Sector Management, 13(2), 402–423. https://doi.org/10.1108/IJESM-11-2017-0006

Al-Azawi, R., Al-Faliti, F., & Al-Blushi, M. (2016). Educational gamification vs. game based learning: Comparative study. International Journal of Innovation, Management and Technology, 7(4), 132–136. https://doi.org/10.18178/ijimt.2016.7.4.659

Alexandre, R., Postolache, O., & Giráo, P. S. (2019, May). Physical rehabilitation based on smart wearable and virtual reality serious game. In 2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) (pp. 1–6). IEEE.

Amaro, A. C., & Oliveira, L. (2019, May). IoT for playful intergenerational learning about cultural heritage: The LOCUS approach. In ICT4AWE (pp. 282–288). Scite Press.

Ardito, C., Buono, P., Desolda, G., & Matare, M. (2018). From smart objects to smart experiences: An end-user development approach. International Journal of Human-Computer Studies, 114, 51–68. https://doi.org/10.1016/j.ijchs.2017.12.002

Ashton, K. (2009). That ‘internet of things’ thing. RFID journal, 22(7), 97–114. https://www.itrco.jp/libraries/RFIDjournal-That%20Internet %20of%20Things%20Thing.pdf

Atzori, L., Iera, A., Morabito, G., & Nitti, M. (2012). The social internet of things (sIoT)—when social networks meet the internet of things: Concept, architecture and network characterization. Computer Networks, 56(16), 3594–3608. https://doi.org/10.1016/j.comnet.2012.07.010

Bahadoor, K., & Hosein, P. (2016, August). Application for the detection of dangerous driving and an associated gamification framework. In 2016 IEEE 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW) (pp. 276–281). IEEE.

Banfield, J., & Wilkerson, B. (2014). Increasing student intrinsic motivation and self-efficacy through gamification pedagogy. Contemporary Issues in Education Research (CIER), 7(4), 291–298. https://doi.org/10.2498/cier.v7i4.8843

Ben-Moussa, M., Rubo, M., Debracque, C., & Lange, W. G. (2017). Djinni: A novel technology supported exposure therapy paradigm for sad combining virtual reality and augmented reality. Frontiers in Psychiatry, 8, 26. https://doi.org/10.3389/fpsyt.2017.00026

Blok, A. C., Valley, T. S., & Abbott, P. (2021). Gamification for family engagement in lifestyle interventions: A systematic review. Prevention Science, 22(7), 1–14. https://doi.org/10.1007/s11121-021-01214-x.

Briones, A. G., Chamoso, P., Rivas, A., Rodríguez, S., De La Prieta, F., Prieto, I., & Corchado, J. M. (2018, August). Use of gamification techniques to encourage garbage recycling, a smart city approach. In International Conference on Knowledge Management in Organizations (pp. 674–685). Springer.

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. Journal of Service Research, 14(3), 252–271. https://doi.org/10.1177/1094670511411703

Brown, P. (2012). A nudge in the right direction? Towards a sociological engagement with libertarian paternalism. Social Policy and Society, 11(3), 305–317. https://doi.org/10.1017/S1474746412000661

Burrows, C. N., & Blanton, H. (2016). Real-world persuasion from virtual-world campaigns: How transportation into virtual worlds moderates in-game influence. Communication Research, 43(4), 542–570. https://doi.org/10.1177/0093650215619215

Büsching, F., Holzhauser, N., Knapp, P., & Wolf, L. (2016, October). A smart spa: Having fun with physical activities. In Proceedings of the 2nd Workshop on Experiences in the Design and Implementation of Smart Objects (pp. 1–5). ACM Press.

### Notes

1. https://ec.europa.eu/digital-single-market/en/policies/internet-things
2. https://ec.europa.eu/research/swafs/index.cfm?pg=policy&lib=engagement
3. https://www.gallup.com/workplace/229424/employee-engagement.aspx
4. https://www.smartcitiesworld.net/news/news/citizen-engagement-is-key-to-smart-city-success-2685

### Disclosure statement

No potential conflict of interest was reported by the author(s).

### Funding

This work was supported by the National Social Science Fund of China [16BGL191]; Academy of Finland [332168]; Business Finland [5654/31/2018].
Henry, J., Tang, S., Hannegham, M., & Carter, C. (2018, May). A framework for the integration of serious games and the Internet of Things (IoT). In 2018 IEEE 6th International Conference on Serious Games and Applications for Health (SeGAH) (pp. 1–8). IEEE.

Hofacker, C. F., De Ruyter, K., Lurie, N. H., Manchanda, P., & Donaldson, J. (2016). Gamification and mobile marketing effectiveness. Journal of Interactive Marketing, 34, 25–36. https://doi.org/10.1016/j.intmar.2016.03.001

Hong, J. K., & Cho, J. D. (2018). The quantified self. The Wiley Handbook of Human Computer Interaction, 2, 909–922. https://doi.org/10.1002/9781118976005.ch42

Honig, W. M., & Eikelboom, R. H. (1985). Microprocessor-based television games, exercises, and evaluation procedures for the physically and mentally handicapped. IEEE Engineering in Medicine and Biology Magazine, 4(4), 43–50. https://doi.org/10.1109MEMB.1985.5006227

Hunnicke, R., LeBlanc, M., & Zubek, R. (2004, July). MDA: A formal approach to game design and game research. In Proceedings of the AAAI Workshop on Challenges in Game AI (Vol. 4, No. 1, p. 1722). AAAI Press.

Hwang, I., Lee, Y., Park, T., & Song, J. (2012, August). Toward a mobile platform for pervasive games. In Proceedings of the first ACM international workshop on Mobile gaming. ACM Press.

Innocent, T. (2016, June). Play in the algorithmic city. In International Conference on Intelligent Technologies for Interactive Entertainment (pp. 266–270). Springer.

Kappelman, L. A., & McLean, E. R. (1994, January). User engagement in the development, implementation, and use of information technologies. In HIHCSS (pp. 512–521). IEEE.

Karime, A., Al-Osman, H., Alja’m, J. M., Gueaieb, W., & El Saddik, A. (2012). Tele-Wobble: A tele-rehabilitation wobble board for lower extremity therapy. IEEE Transactions on Instrumentation and Measurement, 61(7), 1816–1824. https://doi.org/10.1109/TIM.2012.2192338

Kazhamiakin, R., Marconi, A., Martinelli, A., Pistore, M., & Valetto, G. (2016, September). A gamification framework for the long-term engagement of smart citizens. In 2016 IEEE International Smart Cities Conference (ISC2) (pp. 1–7). IEEE.

Kihara, T., Bendor, R., & Lomas, D. (2019, May). Designing an escape room in the city for public engagement with AI-enhanced surveillance. In Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1–6).

Kimura, R., & Nakajima, T. (2019, December). Gamifying human behavior in urban crowdsourcing for a sustainable smart city. In Proceedings of the 21st International Conference on Information Integration and Web-based Applications & Services (pp. 546–555). ACM Press.

Kobeissi, A. H., Sidoti, A., Bellotti, F., Berta, R., & De Gloria, A. (2017, July). Building a tangible serious game framework for elementary spatial and geometry concepts. In 2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT) (pp. 173–177). IEEE.

Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. International Journal of Information Management, 45, 191–210. Elsevier. https://doi.org/10.1016/j.ijinfomat.2018.10.013

Konstantinidis, E. I., Bills, A. S., Mouzakidis, C. A., Zilidou, V. I., Antoniou, P. E., & Bamidis, P. D. (2014). Design, implementation, and wide pilot deployment of FitForAll: An easy to use exergaming platform improving physical fitness and life quality of senior citizens. IEEE Journal of Biomedical and Health Informatics, 20(1), 189–200. https://doi.org/10.1109/JBHI.2014.2378814

Koutsouris, N., Kosmides, P., Demestichas, K., Adamopoulou, E., Giannakopoulou, K., & De Luca, V. (2018, October). InLife: A platform enabling the exploitation of IoT and gamification in healthcare. In 2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob) (pp. 224–230). IEEE.

Krommyda, M., Sologos, E., Tamascelli, S., Tsertou, A., Latsa, G., & Armitis, A. (2018, October). Towards citizen-powered cyberworlds for environmental monitoring. In 2018 International Conference on Cyberworlds (CW) (pp. 454–457). IEEE.

L’Heureux, A., Grolinger, K., Higashino, W. A., & Capretz, M. A. (2017, June). A gamification framework for sensor data analytics. In 2017 IEEE international congress on internet of things (ICIoT) (pp. 74–81). IEEE.

Laine, T. H., & Sedano, C. I. (2015). Distributed pervasive worlds: The case of exergames. Journal of Educational Technology & Society, 18(1), 50–66. http://www.jetsonline.org/index.php/jets/article/view/181150

Landers, N. R., Bauer, K. N., & Callan, R. C. (2017). Gamification of task performance with leaderboards: A goal setting experiment. Computers in Human Behavior, 71, 508–515. https://doi.org/10.1016/j.chb.2015.08.008

Lapao, L. V., Marques, R., Gregório, J., Pinheiro, F., Póvoa, P., & Mira Da Silva, M. (2016, January). Using gamification combined with indoor location to improve nurses’ hand hygiene compliance in an ICU ward. In Transforming Healthcare with the Internet of Things: Proceedings of the EFMI Special Topic Conference (pp. 17–19). https://doi.org/10.3233/978-1-61499-633-0-3

Li, Y., & Lerner, R. M. (2013). Interrelations of behavioral, emotional, and cognitive school engagement in high school students. Journal of Youth and Adolescence, 42(1), 20–32. https://doi.org/10.1007/s10964-012-9537-5

Locke, E. A., & Latham, G. P. (Eds.). (2013). New developments in goal setting and task performance. Routledge.

Looyestyn, J., Kernet, J., Boshoff, K., Ryan, J., Edney, S., & Maher, C. (2017). Does gamification increase engagement with online programs? A systematic review. PLoS One, 12(3), e0173403. https://doi.org/10.1371/journal.pone.0173403

Lu, C. H. (2018). IoT-enabled adaptive context-aware and playful cyber-physical system for everyday energy savings. IEEE Transactions on Human-Machine Systems, 48(4), 380–391. https://doi.org/10.1109/THMS.2018.2844119

Madakam, S., Lake, V., Lake, V., & Lake, V. (2015). Internet of Things (IoT): A literature review. Journal of Computer and Communications, 3(5), 164. https://doi.org/10.4236/jcc.2015.35021

Madar, I. L., Smith, M., & Knackfuss, P. (2014, October). SafeMove – Safe mobility of elderly in the vicinity of their home and on journeys. In International Internet of Things Summit (pp. 151–156). Springer.

Malavade, V. N., & Akulwar, P. K. (2016). Role of IoT in agriculture. IOSR Journal of Computer Engineering, 2016, 2278–2661.

Mann, S., Defaz, D., Abdulazim, T., Lam, D., Alford, M., Stairs, I., Pierce, C., & Mann, C. (2019, June). Encephalograms TM (Brain/Mind Games): Inclusive health and wellbeing for people of all abilities. In 2019 IEEE Games, Entertainment, Media Conference (GEM) (pp. 1–10). IEEE.

Marino, V., & Presti, L. L. (2019). Increasing convergence of civic engagement in management: A systematic literature review. International Journal of Public Sector Management, 32(3), 282–301. https://doi.org/10.1108/IJPSM-03-2018-0068

Martin, A. J. (2012). Part II commentary: Motivation and engagement: Conceptual, operational, and empirical clarity. In S. Christenson S. A. Reschly, & C. Wylie (Eds.), Handbook of research on student engagement (pp. 303–311). Springer.

Massoud, A., Bellotti, F., Berta, R., De Gloria, A., & Poslad, S. (2019, August). Eco-driving profiling and behavioral shifts using iot vehicular sensors combined with serious games. In 2019 IEEE Conference on Games (CoG) (pp. 1–8). IEEE.

Migliano, O., Di Ferdinando, A., Di Fuccio, R., Rega, A., & Ricci, C. (2014). Bridging digital and physical educational games using RFID/NFC technologies. Journal of e-Learning and Knowledge Society, 10(3), 83–104. https://doi.org/10.20368/1971-8829/959

Miranda, J., Mäkitalo, N., Garcia-Alonso, J., Berrocal, J., Mikkonen, T., Canal, C., & Murillo, J. M. (2015). From the internet of things to the internet of people. IEEE Internet Computing, 19(2), 40–47. https://doi.org/10.1109/MIC.2015.24

Miraz, M. H., Ali, M., Excell, P. S., & Picking, R. (2015, September). A review on Internet of Things (IoT), Internet of everything (IoE) and Internet of nano things (IoNT). In 2015 Internet Technologies and Applications (ITA) (pp. 219–224). IEEE.

Monge, J., & Postolache, O. (2018, October). Augmented reality and smart sensors for physical rehabilitation. In 2018 International
Conference and Exposition on Electrical And Power Engineering (EPE) (pp. 1010–1014). IEEE.

Moreno, M., Ubeda, B., Skarmeta, A. F., & Zamora, M. A. (2014). How can we tackle energy efficiency in iot based smart buildings? Sensors, 14(6), 9582–9614. https://doi.org/10.3390/s14069582

Morschheuser, B., Hanari, J., Koivistö, J., & Maedche, A. (2017). Gamified crowdsourcing: Conceptualization, literature review, and future agenda. International Journal of Human-Computer Studies, 106, 26–43. https://doi.org/10.1016/j.ijhcs.2017.04.005

Mylonas, G., Amxalilatis, D., Pocero, L., Markelis, I., Hofstaetter, J., & Koulouris, P. (2019). An educational IoT lab kit and tools for energy awareness in European schools. International Journal of Child-Computer Interaction, 20, 43–53. https://doi.org/10.1016/j.jicc.2019.03.003

Ng, I. C., & Wakenshaw, S. Y. (2017). The Internet-of-Things: Review and research directions. International Journal of Research in Marketing, 34(1), 3–21. https://doi.org/10.1016/j.ijresmar.2016.11.003

Ng, S. C., Sweeney, J. C., & Plewa, C. (2020). Customer engagement: A systematic review and future research priorities. Australasian Marketing Journal (AMJ), 28(4), 235–252. https://doi.org/10.1016/j.ajmj.2020.05.004

O’Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. Journal of the American Society for Information Science and Technology, 59(6), 938–955. https://doi.org/10.1002/asi.20801

O’Brien, H. (2016). Theoretical perspectives on user engagement. In Why engagement matters (pp. 1–26). Springer.

Oliver, M., Teruel, M. A., Molina, J. P., Romero-Ayuso, D., & González, P. (2018). Ambient intelligence environment for home cognitive telecarehabilitation. Sensors, 18(11), 3671. https://doi.org/10.3390/s18113671

Oliveri, M., Hauge, J. B., Bellotti, F., Berta, R., & De Gloria, A. (2019, June). Designing an IoT-focused, multiplayer serious game for industry 4.0 innovation. In 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1–9). IEEE.

Oğan, E. (2015). Teaching and promoting smart internet of things solutions using the serious-game approach. In D. Sharma, M. Favorskaya, L. C. Jain, & R. J. Howlett (Eds.), Fusion of smart, multimedia and computer gaming technologies (pp. 73–90). Springer.

Palakavanga-Na-Ayudhya, S., Pongchandaj, S., Kriangaksadakai, S., & Sunthornwuthikrai, K. (2017, November). KeptAom: Savings management system to increase long term savings behavior of children. In TENCON 2017–2017 IEEE Region 10 Conference (pp. 2247–2252). IEEE.

Papaioannou, T. G., Dimitriou, N., Vasilakis, K., Schoofs, A., Nikiforakis, M., Pursche, F., Deliyski, N., Taha, A., Kotsopoulos, D., Bardaki, C., Kotsilits, S., & Garbi, A. (2018). An IoT-based gamified approach for reducing occupants’ energy wastage in public buildings. Sensors, 18(2), 537. https://doi.org/10.3390/s18020537

Pargman, D., Ringenson, T., Rivera, M. B., Schmitz, L., Krinaki, M., Prekratic, N., & Lundkvist, B. (2017, June). Smart magic city run: Exploring the implications of public augmented reality games. In International Conference on Intelligent Technologies for Interactive Entertainment (pp. 151–158). Springer.

Penders, A., Octavia, J. R., Caron, M. de, Haan, F., Devogdert, T., Nop, S., McAtear, A., Pieters, O., Wyffels, F., Verstockt, S., & Saldien, J. (2018, October). Solis: A smart interactive system for houseplants caring. In 2018 International Conference on Orange Technologies (ICOT) (pp. 1–7). IEEE.

Pokric, B., Krco, S., Drajić, D., Pokric, M., Rajas, V., Mihajlović, Z., Knezevic, P., & Jovanovic, D. (2015). Augmented reality enabled iot services for environmental monitoring utilising serious gaming concept. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 6(1), 37–55.

Poslad, S., Ma, A., Wang, Z., & Mei, H. (2015). Using a smart city IoT to incentivize and target shifts in mobility behaviour—Is it a piece of pie? Sensors (15), 13069–13096. https://doi.org/10.3390/s150613069

Postolache, G., Carry, F., Lourenço, F., Ferreira, D., Oliveira, R., Girão, P. S., & Postolache, O. (2019). Serious games based on kinect and leap motion controller for upper limbs physical rehabilitation. In S. Mukhopadhyay, K. Jayasundera, & O. Postolache (Eds.), Modern sensing technologies (pp. 147–177). Springer.

Pourazadan, M., Fiandrino, C., Kantarci, B., Sotya, T., Kliazovich, D., & Bouvy, P. (2017). Intelligent gaming for mobile crowd-sensing participants to acquire trustworthy big data in the internet of things. IEEE Access, 5, 22209–22223. https://doi.org/10.1109/ACCESS.2017.2762238

Pozzi, M., & Sgardelis, P. (2016, September). Engaging Self-powered Environmental Sensors via Serious Gaming. In International Conference on Applications in Electronics Pervading Industry, Environment and Society (pp. 34–40). Springer.

Quintas, A., Martins, J., Magalhães, M., Silva, F., & Analide, C. (2016). Intelligible data metrics for ambient sensorization and gamification. In Intelligent distributed computing IX (pp. 333–342). Springer.

Radeta, M., Ribeiro, M., Vasconcelos, D., & Nunes, N. J. (2019, November). LoRattle: An exploratory game with a purpose using LoRa and IoT. In Joint International Conference on Entertainment Computing and Serious Games (pp. 263–277). Springer.

Rho, S., & Chen, Y. (2018). Social internet of things: Applications, architectures and protocols. Elsevier.

Reck, V., Zhou, Y., Mustafa, N., Menon, N. A., & Eid, M. (2015, October). ECO ECO: Changing climate related behaviors for cellphone-based videogames. In 2015 IEEE International Symposium on Haptic, Audio and Visual Environments and Games (HAVE) (pp. 1–5). IEEE.

Rowland, S. (2015, September). BIM to IoT: The persistence problem. In International Conference on Serious Games, Interaction, and Simulation (pp. 127–137). Springer.

Schmidt, M., Benzing, V., & Kamer, M. (2016). Classroom-based physical activity breaks and children’s attention: Cognitive engagement works! Frontiers in Psychology, 7, 1474. https://doi.org/10.3389/fpsyg.2016.01474

Song, H., Lee, S., Kim, H., Jiang, G., Choi, Y., & Yang, D. (2016, May). Rafael: Wearable technology and serious game for rehabilitation. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 3774–3777). ACM Press.

Spyrou, E., Vretos, N., Pomazanekyi, A., Asteriadis, S., & Leligou, H. C. (2018, August). Exploiting IoT technologies for personalized learning. In 2018 IEEE Conference on Computational Intelligence and Games (CIG) (pp. 1–8). IEEE.

Stepanovic, S., & Mettler, T. (2018, June). Gamification applied for health promotion? Does it really foster long-term engagement? A scoping review. In Proceedings of the 26th European Conference on Information Systems (pp. 1–16). AIS.

Tan, V., & Varghese, S. A. (2016, June). IoT-enabled health promotion. In Proceedings of the first workshop on IoT-enabled healthcare and wellness technologies and systems (pp. 17–18). ACM Press.

Thaler, R. H., & Sunstein, C. R. (2010). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.

TongKe, F. (2013). Smart agriculture based on cloud computing and IOT. Journal of Convergence Information Technology, 8(2), 210–216. https://doi.org/10.4156/jcit.vol8.issue2.26

Tziortzioti, C., Andreotti, G., Rodnò, L., Mavrommati, I., Vitalletti, A., & Chatzigiannakis, I. (2018, November). Raising awareness for water polution based on game activities using internet of things. In European Conference on Ambient Intelligence (pp. 171–187). Springer.

Uskov, A., & Sekar, B. (2015). Smart gamification and smart serious games. In D. Sharma, M. Favorskaya, L. C. Jain, & R. J. Howlett (Eds.), Fusion of smart, multimedia and computer gaming technologies (pp. 7–36). Springer.

Van Der Helm, A. (2008). Experience design for interactive products: Designing technology augmented urban playgrounds for girls. Psychology and Computing, 6(2), 173–188.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoeof, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. Journal of Service Research, 13(3), 253–266. https://doi.org/10.1177/1094670510375599

Vetter, M., & Kutzner, F. (2016). Nudge me if you can—how defaults and attitude strength interact to change behavior. Comprehensive Results
in Social Psychology, 1(1–3), 8–34. https://doi.org/10.1080/23743603.2016.1139390

Wang, Y., & Hu, W. (2017, May). Analysis about serious game innovation on mobile devices. In 2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS) (pp. 627–630). IEEE.

Weiser, M. (2002). The computer for the 21st century. IEEE Pervasive Computing, 1(1), 19–25. https://doi.org/10.1109/MPRV.2002.993141

Westgate, E. C., & Wilson, T. D. (2018). Boring thoughts and bored minds: The MAC model of boredom and cognitive engagement. Psychological Review, 125(5), 689. https://doi.org/10.1037/rev0000097

Wilkowska, W., Jakobs, E. M., & Ziefle, M. (2015). Acceptance of eHealth technology in home environments: Advanced studies on user diversity in ambient assisted living (No. RWTH-2016-01550). Lehrstuhl für Kommunikationswissenschaft.

Williams, M., Nurse, J. R., & Creese, S. (2019). (Smart) Watch Out! Encouraging privacy-protective behavior through interactive games. International Journal of Human-Computer Studies, 132, 121–137. https://doi.org/10.1016/j.ijhcs.2019.07.012

Winnicka, A., Kęsik, K., Polap, D., Wosiak, M., & Marszałek, Z. (2019). A multi-agent gamification system for managing smart homes. Sensors, 19(5), 1249. https://doi.org/10.3390/s19051249

Xu, F., Buhalıs, D., & Weber, J. (2017). Serious games and the gamification of tourism. Tourism Management, 60, 244–256. https://doi.org/10.1016/j.tourman.2016.11.020

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. American Educational Research Journal, 29(3), 663–676. https://doi.org/10.3102/0291922X029003663

Zukin, C., Keeter, S., Andolina, M., Jenkins, K., & Carpini, M. X. D. (2006). A new engagement: Political participation, civic life, and the changing American citizen. Oxford University Press.

About the Authors

Ruwei Xiao is a postdoctoral researcher at Tampere University, Finland. She has a Ph.D of Media Design from Keio University, Japan. Previously, she also worked for one of the major Japanese game manufacturers, KOEITECMO.

Zhanwei Wu is an associate professor in the School of Design at Shanghai Jiao Tong University. He holds a PhD in Digital Media from Shanghai Jiao Tong University, and his research interests include behavior informatics and design.

Juho Hamari is a professor of Gamification at Tampere University and the head of the Gamification Group. He has authored several seminal empirical, theoretical and meta-analytical scholarly articles on several topics related to gameful phenomenon from the perspectives of consumer behavior, human-computer interaction, game studies, and information systems science.
## Appendix A. Detailed results of each empirical research

| Reference Number | Domain | Participants | Cognitive-behavioral Engagement Outcome | Engagement Scale | Engagement Stage | Engagement Measurement | System Factors | Factor measurement |
|------------------|--------|--------------|----------------------------------------|------------------|-----------------|------------------------|----------------|-------------------|
| (Agyeman & Al-Mahmood, 2019) | Health Care/Well being | 8 | Attitude: Most participants agree that leG is useful and feasible to help in the rehabilitation process of stroke patients | Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | Questionnaire | General usability | SUS, NPS, NASA-TLX self-report |
| (Ardivi et al., 2018) | Tourism | 14 | | | | | | |
| (Bahadoor & Hosen, 2016) | Skill training | 6 | Attitude: users reported 100% positive feedback, some features are reported to be useful | Multi-user Engagement Individual Engagement | Period of Sustained Engagement, Long-term Engagement | Self-report, questionnaire | Social incentive: 100% participants report social feed and discount reward are useful, Interactivity: 67% participants report that interactive map is useful | Questionnaire, system log |
| (Wilkska et al., 2015) | Health Care/Well being | 64 | Attitude: users report that the system is usefulMotivation: The more users use the system, the stronger the willingness to continue using | Individual Engagement | Period of Sustained Engagement, Long-term Engagement | Self-report, system log | Social incentive: need for achievement is reported as a determinant of behavior in multiple regression analysis, | Questionnaire, system log |
| (Briones et al., 2018) | Sustainability | 1819 | Behavior: recycled waste amount increased 17.2% in pre-post comparison (performance), participation increased by 32.2% (frequency) | Multi-user Engagement | Point of Sustained Engagement, Long-term Engagement | System log | | |
| (Casals et al., 2017) | Sustainability | 80 (control group 40, experiment group 40) | Behavior: experiment group showed statistically more energy saving in experiment-control group comparison (Performance) | Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | System log | Intrinsic incentive: Tenants who achieved higher game scores and completed more missions achieved higher electricity savings | System log |
| (Chen et al., 2017) | Crowd Sourcing | 4 | Attitude: participants report leG is more enjoyable and attractive than traditional app | Public Engagement | Engagement, Period of Sustained Engagement | Self-report, questionnaire | | |
| (Dange et al., 2016) | Skill training | Unknown | Behavior: better driver behavior pattern is detected after using leG system (performance) | Multi-user Engagement | Period of Sustained Engagement | System log | | |
| (Dessureault, 2019) | Industry | Unknown | Behavior: 30–76% productivity improvement in pre-post comparison (performance), expected operation increased 233% (frequency) | Multi-user Engagement | Period of Sustained Engagement | System log | | |
| (Garcia et al., 2017) | Sustainability | 18 | Behavior: energy consumption per day decreased 6.6% during the 30 days experiment (performance) | Multi-user Engagement | Period of Sustained Engagement | System log | | |
| (Henry et al., 2018) | Education | 22 (Control group 11, experiment group 11) | Behavior: experiment group has 55% more response rate in experiment-control group comparison (performance) | Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | System log | | |
| (Hwang et al., 2012) | Health Care/Well being | 32/11 | Attitude: participants have positive feedback and agree that the system is helpful to exercise behavior: more conversation observed in proposed system than standard level (frequency) | Individual Engagement, Multi-user Engagement | Period of Sustained Engagement | Video based behavior analysis, interview | Immersive appeal: participants strongly agreed that physical interaction game helped them better immersed in exercises | |
| (Karime et al., 2012) | Health Care/Well being | 21 (20 healthy users, 1 patient) | Behavior: patients have overall better performance to finish Rehabilitation tasks during the 14-days experiments (performance) | Multi-user Engagement | Period of Sustained Engagement | System log | | |
| | | | | | | | | | (Continued) |
| Reference Number | Domain                                      | Participants                                      | Cognitive-behavioral Engagement Outcome                                                                 | Engagement Scale | Engagement Stage                  | Engagement Measurement | System Factors | Factor measurement |
|------------------|---------------------------------------------|---------------------------------------------------|----------------------------------------------------------------------------------------------------------|------------------|----------------------------------|------------------------|----------------|---------------------|
| (Kazhamiakin et al., 2016) | Sustainability, Transportation             | 300 (100 active participants, 36 survey respondents) | attitude: 63% participants report the proposed system changed their mobility habit motivation: 81% participants intend to keep the new habits in the future behavior; sustainable mobility behavior increased frequency, IeG system has better acceptance of recommendation than traditional system attention: privacy awareness increased from 2.75 to 3.25 averagely in 5-point Likert scale; attention: anti-surveillance attitude increased from 3.25 to 4.25 averagely; | Public Engagement | Point of Engagement, Period of Sustained Engagement, Long-term Engagement | self-report, system log | Novelty appeal: Behavior frequency changed when challenge theme changed, system log |                      |
| (Khara et al., 2019) | Education                                  | 4                                                 |                                                                                                         | Public Engagement | Point of Engagement              | interview, self-report  |                |                     |
| (Lapão et al., 2016) | Skill training                              | 4                                                 | attention: increased compliance awareness among participants is reported; behavior: increased compliance behavior is reported frequency; | Multi-user Engagement | Point of Engagement, Long-term Engagement | interview               |                |                     |
| (L’Heureux et al., 2017) | Crowd Sourcing, Smart Building              | 86 gaming actions                                  | behavior: participants reported the system changed their wasteful consumption habits (performance), 72.6% actions in the system helped to crowd-sourced data labeling (frequency). Behavior: energy consumption decreased 16.21–37% (performance) | Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | interview, system log  |                |                     |
| (Lu, 2018) | Smart Home/ Home Automation, Sustainability | 22 for each simulation test                        |                                                                                                         | Individual Engagement | Point of Engagement, Period of Sustained Engagement, Long-term Engagement | system log             | Accessibility: adaptive contextual awareness feature had impact on behavior | system log, interview |
| (Miglino et al., 2014) | Education                                  | Test I: 257 students, 2 children, 10 teacherTest II: 1 girl with multiple disabilitiesTest III: 52 students | attitude: participants prefer IeG than traditional method behavior: no statistical difference was found when comparing learning performance in IeG system and system using traditional approach | Multi-user Engagement | Point of Engagement, Period of Sustained Engagement, Long-term Engagement | observation, interview | Immersive appeal: children are observed to be more involved in learning process, Social incentive: learners report more fun and socializing perception | observation, self-report |
| (Mylonas et al., 2019) | Education, Sustainability                   | 106 students for workshop in total, 7 teachers for questionnaire, 5 teachers for interview | attitude: 84% and 94% students in two workshop report the system is engaging, 98% and 96% report the system is useful behavior: learning performance | Multi-user Engagement | Point of Engagement, Period of Sustained Engagement, Long-term Engagement | self-report, questionnaire | Social incentive (Competition, social network) not reported and Interactability (awareness, recommendation) are hypothesized to strengthen engagement, however no empirical evidences are provided | questionnaire |
| (Oliver et al., 2018) | Health Care/ Well being                    | 20                                                | attitude: expert satisfaction scored 8.76/10                                                         | Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | Questionnaire; Expert Rating; interview | General usability | questionnaire |
| (Oliver et al., 2019) | Education, Industry                        | 11 in total (4 in final test)                      | attitude: participants report interests in the system behavior; increased learning outcomes in pre-post comparison (performance) | Individual Engagement, Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | interview General usability |                |                     |
| (Palavangsa-Na-Ayudhya et al., 2017) | Education, Economic                      | Unknown                                           | Motivation: Expert admit that the system can motivate children to start money saving                  | Multi-user Engagement | Point of Engagement, Period of Sustained Engagement, Long-term Engagement | Expert rating            |                |                     |
| Reference Number | Domain                  | Participants | Cognitive-behavioral Engagement Outcome | Engagement Scale | Engagement Stage | Engagement Measurement | System Factors                          | Factor Measurement |
|------------------|-------------------------|--------------|----------------------------------------|------------------|------------------|------------------------|----------------------------------------|-------------------|
| (Papaioannou et al., 2018) | Sustainability | 120 (40 from each pilot site) | Attitude: the system is welcomed by the target users | Multi-user Engagement | Point of Engagement, Period of Sustained Engagement | interview | Comprehensiveness: participants respond positively to the usage simplicity |
| (Pokric et al., 2015) | Education, Sustainability | 23 | Attitude: users respond positively to the proposed leG system | Individual Engagement | Point of Engagement, Period of Sustained Engagement | questionnaire | Social network features are rated best, however there is no proof that sharing information and experiences contribute to shifting travel behavior |
| (Poslad et al., 2015) | Sustainability, Transportation | 268 (Enschede), 112 (Leeds), 138 (Gothenburg) | Attitude: 50% participants report the system tasks are irrelevant and 30–50% report tasks are unfeasible; behavior: 46% participants finished tasks, 34% got the reward (a pie) | Public Engagement | Period of Sustained Engagement, Long-term Engagement, Nonengagement | self-report, questionnaire, system log | |
| (Postolache et al., 2019) | Health Care/Well being | 8 | Attitude: participants report general positive opinions about the system; motivation: participants consider that the system can increase patients’ motivation for rehabilitation | Multi-user Engagement | Period of Sustained Engagement | Questionnaire; Expert Rating; | |
| (Pozzi & Sgardelis, 2016) | Crowd Sourcing | unknown due to technical trouble | Attention: large number of interaction records show passersby’s attention is attracted; behavior: low number of targeted behavior records show public is reluctant to engage (frequency) | Public Engagement | Period of Sustained Engagement, Nonengagement | analysis from interaction record | |
| (Tan & Varghese, 2016) | Health Care/Well being | 3000 in pilot, 156000 in national challenge | Behavior: increased and sustained target activities are reported in pre-post comparison (frequency) | Public Engagement | Period of Sustained Engagement, Nonengagement | system log | |
| (Williams et al., 2019) | Skill training | 504 | Attitude: no statistical difference is reported in pre-post comparison of privacy concern; behavior: significant difference is reported in pre-post comparison of certain privacy protection behaviors (frequency) | Individual Engagement | Period of Sustained Engagement, Long-term Engagement, Nonengagement | questionnaire, system log | |
| (Winnicka et al., 2019) | Smart Home/Home Automation | 3 families | motivation: participants report 8.33 out of 10 scale motivation to adopt the proposed system | Multi-user Engagement | Period of Engagement, Long-term Engagement, Nonengagement | self-report | Social incentive (competition): participants agree that competition can enhance their motivation (average 8.33 of 10 scale) |
| (Rock Zou et al., 2015) | Education, Sustainability | 13 in total | motivation: young children are reported to be motivated to follow green habits | Individual Engagement | Period of Engagement, Period of Sustained Engagement, Long-term Engagement, Nonengagement | observation, interview | |
| (Kimura & Nakajima, 2019) | Sustainability, Crowd Sourcing | 4 | | Multi-user Engagement | Period of Engagement, Period of Sustained Engagement, Long-term Engagement | focus group interview | Intrinsic incentive: participants report that virtual rewards did not affect their motivation |
| Reference Number | Domain                        | Participants | Cognitive-behavioral Engagement Outcome                                                                 | Engagement Scale                        | Engagement Stage        | Engagement Measurement | System Factors                     | Factor measurement |
|------------------|-------------------------------|--------------|---------------------------------------------------------------------------------------------------------|----------------------------------------|-------------------------|------------------------|-----------------------------------|-------------------|
| (Alexandre et al., 2019) | Health Care/Well being | 2            | Behavior: The more users use the system, the higher the score each time (performance)                    | Multi-user Engagement                  | Period of Sustained Engagement | System log             | General usability: SUS score is 70.88/100 | SUS               |
| (Radeta et al., 2019)       | General Purpose, Entertainment | 20           | Attention: radio coverage perception increased to 35% of participants, remaining the same for 50%, while decreasing to 15% | Multi-user Engagement                  | Period of Sustained Engagement | Interview, questionnaire | General usability: SUS score is 76.36/100 | SUS               |
| (Konstan-tidis et al., 2014) | Health Care/Well being | 116 intervention, 116 control group | Motivation: 92.2% reported that the platform worth paying if it was ever marketed. Behavior: Adherence is 82% and the training efficacy of intervention group is statistically higher than control group. | Multi-user Engagement, Individual Engagement, Multi-user Engagement | Period of Sustained Engagement, Long-term Engagement | System log, questionnaire | General usability: SUS score is 76.36/100 | SUS               |