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A Digital Collaborative Game to Facilitate Learning about Open Data

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As Ian Bogost claims, games make rhetorical arguments in a procedural form. You can accept their portrayals as truthful, or reject them when they clash with your own mental models. To me, the most valuable part of playing a game like SimCity is not that it explains how a city works, but rather, that it forces you to examine your own mental model of a city.

PAOLO PEDERCINI (2019)

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Abbreviations

API	Application Programming Interface
FLoC	Federated Learning of Cohorts
FOI	Freedom of Information
LM-GM	Learning Mechanics-Game Mechanics
ODP	Open Data Policy
OGD	Open Government Data

1 Summary

Governments are trying to release more open government data to the public. Opening data is in line with the principles of open government and facilitates transparency, accountability and the creation of new public tools made by citizens and private entities. However, releasing datasets requires the participation of civil servants across different levels of government and in different organisations, who need to be trained about the risks and benefits of open data. Serious games - especially those that leverage the benefits of collaborative learning - offer a viable tool to deliver training and achieve learning and have been previously used in the context of Open Government Data (OGD). With the onset of the COVID-19 pandemic, in-person participation to game sessions was temporarily hindered. None of the serious games about OGD found in the literature were designed to be played remotely. Therefore, this research was aimed at understanding the requirements for a digital (remote) serious game about OGD, developing it and measuring its learning outcomes. Chapter 3 analysed the existing literature on OGD and serious games. It was found that open data increases government transparency and gives citizens the opportunity to build public tools and analyse societal issues. At the same time, opening data involves risks to individual and group privacy, chilling effects and social sorting. Civil servants who are tasked with opening datasets need to evaluate these complex trade-offs but are often understaffed and take decisions under real and perceived barriers regarding legal and hierarchical risks and liabilities. Therefore, a tool for training civil servants about the risks on benefits of OGD is needed. Serious games were found to be an important solution, especially when they leverage collaborative earning. In order to develop a serious game and to assess it outcomes, the in-person collaborative game Winning Data (Kleiman et al. 2019) was chosen as basis, given the quasi-experimental evidence that supports it is helpful to achieve learning outcomes.

In Chapter 4 the perspective new game prorotype was mapped using the LM-GM framework by Arnab et al. (2015). A one group pre-test post-test quasi-experiment was chosen to evaluate the game's learning outcomes, using surveys adapted from Kleiman et al. (2020).

As shown in Chapter 5, the game was played remotely by 28 civil servants from Europe and Brazil, who filled pre-test and post-test surveys in order to assess the learning outcomes of the game. As discussed in Chapter 6, the results from the quasi-experiment highlight that are are two main requirements for a digital game: collaboration, which had an impact on the feeling of support from colleagues, and questions & answers, which encouraged knowledge sharing among players. With regards to the learning objectives, results seem to indicate that participants were more willing to open data and more aware

about the benefits and risks of doing so. Findings are mainly limited by the lack of a control group and small sample size.

This research showed how an in-person serious game can be transformed into an online interaction while preserving its collaborative elements. The online environment introduced several challenges and limitations. Still, the online game managed to encourage knowledge sharing among players, who discussed the possible benefits and risks of opening certain datasets.

2 Introduction

Government data is "any data and information produced or commissioned by public bodies" (Ubaldi 2013). Government data can be considered open "if anyone is free to access, use, modify, and share it" (Open Knowledge Foundation). OGD is a valuable tool to build new or better public and private services, and also to increase public transparency of government (Ubaldi 2013).

Generating open data requires civil servants in different bodies and at different levels of government to correctly identify suitable data and make a decision to release it, all while taking into account possible legal, liability and privacy risks (Crusoe and Melin 2018).

European governments have been enacting Open Data Policies (ODPs) with the aim of facilitating the disclosure of public sector data from governmental organisations. While ODPs are usually enacted in a top to bottom fashion, a successful approach requires the engagement of all levels of government, including the municipal and provincial level, which are also involved in collecting and releasing government data (Ubaldi 2013). In order to support the release of open data, local level civil servants need to be aware about the benefits and risks of open data so they can make informed decisions about whether or not to disclose information coming from the public sector.

Serious games have been identified as a tool with promising potential for training civil servants, while at the same time offering an opportunity to conduct quasi-experiments and gather both qualitative and quantitative data (de Caluwé et al. 2012). For example, Bharosa et al. (2010) created a game to simulate service delivery in the public sector. The game was played by public employees, who then synthesised principles for service delivery based on their experience.

In the field of open data, several serious games have been developed to train civil servants. Datopolis (Broad and Tennison 2015) is board game in which players need to negotiate and combine datasets in order to build tools and applications based on open data. Winning Data (Kleiman et al. 2019), is a less common example of a game about open data developed both for training and for research. In Winning Data, players are assigned roles and interact together in the simulated environment of a public office. With the onset of the COVID-19 pandemic, in-person participation was temporarily hindered, and the need for a game that can played remotely arose. Consequently, this paper is focused on addressing two issues: (1) the need to translate in-person gamified training activities into an online remote environment and (2) the need for a serious game on the topic of open data that is useful for training civil servants.

To address these issues, a new serious game called Data Belt was developed both with the aim of training civil servants about open data decision-making and to research its learning outcomes and wider potential of serious games for training. The game is heavily based on Winning Data and can be considered its digital version. This paper will discuss how the in-person game mechanics and learning mechanics have been transposed into the online remote environment. To assess the viability of collaborative digital serious games as a training tool, the learning outcomes of Data Belt have been analysed using pre-test and post-test surveys adapted from Kleiman et al. (2019). This research is a continuation of Di Staso et al. (a), which presented the design and main features of Data Belt, and of Di Staso et al. (b), which contains a partial analysis of the data collected for this thesis.

A total of 52 people were involved in 13 game sessions played remotely in a quasi-experimental setting. Graduate students were invited to play first, so that the game could be tested and debugged. After the game and the research procedure were refined, civil servants from EU institutions and governmental bodies of the Netherlands and Brazil were invited to play. A sample of 28 civil servants played the game and filled both the pre-test post-test surveys. A paired samples *t*-test was conducted comparing the pre-test and post-test mean of each Likert item. A different set of Likert items (present only in the post-test questionnaire) asked participants to self-report acceptance of the game and learning outcomes.

The game was found to be effective at stimulating group discussions between players on the topic of releasing datasets. At the same time, the pre-test and post-test analysis showed that participants were more inclined to think that some public sector data can be shared and also more aware about its benefits and risks. Participants had high acceptance of the game, but - on average - did not self-report significant learning outcomes. Further research is needed to investigate the contrast between the findings in the pre-test post-test analysis and in the self-reported items.

2.1 Research objectives and research questions

This research is mainly aimed at transposing a serious game on the topic of open data into an online remote environment and assessing its learning outcomes. Therefore, two research questions were formulated:

(1) What are the requirements for the design of a digital serious game on the topic of open data?

(2) Which learning outcomes can be observed in civil servants who played the game?

The first research question ("What are the requirements for the design of a digital serious game on the topic of open data?) is about analysing a pre-existing in-person game on the topic of open data and gathering design requirements in the form of game and learning mechanics and essential features. The game to be used as a starting point is Winning Data (Kleiman et al. 2019). Serious games are defined as games in which the main purpose is something other than pure entertainment (Michael and Chen, 2005, as cited in Laamarti et al., 2014). The main aim of the serious game developed for this research is to convey to players that releasing OGD has benefits and risks.

The second research question ("Which learning outcomes can be observed in civil servants who played the game?") is about understanding if the game successfully conveyed its message, leading to the achievement of the expected learning outcomes.

In order to answer these questions, this thesis will be organised as follows: in Chapter 3 the concept of OGD will be defined, along with its public value, applications, risks and barriers to adoption. Literature on serious games and games for government will then be presented, along with the principles of game-based learning and collaborative learning. Chapter 4 will present the objectives of this research, the methodology used to develop the game and to assess its learning outcomes. Chapters 5 and 6 will present and discuss the results of the data analysis. Finally, Chapter 7 will show the conclusions and limitations of this research and propose ideas for future work.

3 Research theories and background

3.1 Introduction

The following chapter will present the existing literature on OGD, along with examples of useful applications and benefits that it can bring. Threats and risks of opening data - such as privacy violations and chilling effects - will also be presented. This chapter will also discuss barriers to the opening of data before introducing serious games as a possible solution in a government setting. Existing serious games on the topic of open data will be presented along with the benefits of collaborative learning.

3.2 Open government data

In order for data to be truly "open", it should have a license allowing for reuse and redistribution without limitations. Most government data portals apply some variation of the Creative Commons license. For example, the European Open Data Portal uses the CC BY 4.0 license, which allows users to freely share and adapt datasets, as long as appropriate credit is given and there is clear indication of any changes made to the dataset. Bunakov and Jeffery (2013) observed that European states adopt a variety of licenses for the data shared on their open data portals. For example, France applies the "License Ouvert" for all the public sector information offered on its portal, whereas Germany lets governmental agencies pick the most appropriate license for each dataset (Bunakov and Jeffery 2013). Among the different - and sometimes unique - licensing arrangements in use, some common patterns were observed, such as giving permission to transform, re-distribute and re-use data (including for commercial purposes), as well as requiring proper attribution (Bunakov and Jeffery 2013).

According to the Open Knowledge Foundation, for data to be considered "open" it must be:

- In the public domain or covered by open license (which should permit, among other things, free use, redistribution and modification)
- In a form that can be read by a machine
- In a format that can be used freely and that can be read by an open-source software tool

The requirements listed above are themselves derived from the principles of the Open Source Definition, which is commonly used for software.

OGD can contain information about an array of different topics, such as weather, school attendance, public buildings and others. The release of some OGD is nowadays taken for granted and is employed in important day to day tools such as maps and weather forecasting. Over time, more and more government bodies have started sharing their data with the public and open data portals such as data.europa.eu emerged to organise and publicise datasets.

OGD can be either distributed as static datasets or as a dynamic Application Programming Interface (API). If data is released through an API, it is much easier for users who know how to program to update the data as needed or integrate it into an application. A further method to disclose data with the public is to use a feed, in which a dataset is periodically updated (sometimes very frequently) so that users can always access the latest version. Choosing the appropriate method depends on the kind of dataset to be disclosed and its expected usage.

In general, OGD can help governments by engaging citizens and the wider society in the creation and delivery of public services (Ubaldi 2013). According to Janssen et al. (2012), if OGD is released and publicised properly, a positive feedback loop can happen in which the public takes part in data processing, enriches and combines datasets with information from other sources and even participates in the data collection. When this happens, the boundaries between public organisations and the public begin to disappear and the traditional closed system gives way to an open system (Janssen et al. 2012).

3.2.1 Applications and benefits

It is impossible to determine the exact value of opening data or how much economic activity it will generate a priori (Janssen et al. 2012). Without precise incentives and metrics, some organisations tend to aim for a certain target of datasets to be opened and overlook the quality of the data that is being released (Luthfi et al. 2020).

There are some general motivations for the opening of data, Janssen et al. (2012) categorises them as either: political and social, economic, operational and technical. Political and social benefits include increased government transparency, trust and accountability (Janssen et al. 2012). From the economic point of view, opening data can lead to greater innovation, improved products and services and even - in the case of "killer applications" - the creation of entirely new business sectors (Janssen et al. 2012). Still, the benefits obtained by opening data should only be evaluated by looking at each instance individually (Janssen et al. 2012).

Today a number of businesses rely on public sector data to provide their services. Geographical information has traditionally been used by companies involved in utilities, telecommunications, transport and the banking and real estate sector (Fornefeld et al. 2008). As described in Kassen (2013), the city of Chicago opened its own open data portal and started offering the city's datasets to its citizens, leading to the creation of several useful tools and applications. For example, the now defunct chicagolobbyists.org (Open City 2012) aggregated publicly available information about lobbying activities in the city, publishing lists about the most paid lobbyists and most active clients, thus transforming obscure datasets into accessible information for citizens and journalists. Sweeparound.us (Robbin & Co) is another service born out of Chicago's open data and is still active at the time of writing, it provides information about street sweepings so that residents can move out their cars and avoid fines, complete with a map and email notifications. The entire project is itself open-source and - should the original maintainer stop hosting it - anyone could access the source code and run it themselves. Open data has also enabled innovative tools for public transportation. Kuhn (2011) showed that even with imprecise realtime location data about public transit vehicles, it is possible to analyse service levels to identify issues such as bus bunching or give predictions about arrivals, a feature that is now commonplace in most transit apps.

Successful projects using OGD have also originated from datathons. Datathons are based on the concept of hackathons, which were born in the Silicon Valley to generate ideas and collaboration within a very limited timeframe (Aboab et al. 2016). During dathathons, participants form teams to analyse and visualise pre-existing datasets in order to answer a given research question (Aboab et al. 2016). In order to stimulate the use of open data, the European Union organises a yearly EU Datathon, publishing challenges and awarding monetary prizes to the winning teams (Publications Office of the European Union 2021).

Some examples of projects born during datathons follow. Matassoni (2021) created visualisations of OGD on gender-based violence in Italy, showing that victims are almost equally spread across all ages and that some regions in the country's south are lacking data. Ferrini et al. (2021) created interactive data visualisations to explain the ecological impact of fishing. The project uses open data on the presence of fishing vessels, employment numbers for aquaculture and other datasets to paint on overall image of the fishing footprint.

3.2.2 Threats and risks

Zuiderwijk and Janssen (2014) list several aspects of the "dark side of opening data", such as the inherent risk of violating laws and regulations, which can be even greater when several organisations contributed to the data collection for a certain dataset. Having more than one contributing organisation also makes it difficult to establish data ownership, consequently deterring the release of data in order to avoid reputational damage (Zuiderwijk and Janssen 2014).

Zuiderwijk and Janssen (2014) also describe unintentional privacy violations, such as the disclosure of datasets that contain enough data to identify specific individuals. Even when a single dataset is not specific enough, it may be combined with other datasets - present or future - in order to perform identification, thereby creating unexpected privacy issues (Zuiderwijk and Janssen 2014). To give an example:

> Suppose that we publish the mean age of sex offenders each year, and that it is possible to categorize the mean age according to gender in a city. If each city also publishes its local crime statistics each year and there is one female sex offender in a certain year then the age of this female [individual] can be exposed easily by means of a mash up application. Depending on the knowledge that can be gathered, such as her profession, one may expose the full identity of such a person, and therefore violate the privacy law (Kalidien et al. 2010).

When individuals cannot be uniquely identified by a single dataset or a combination of datasets, there is still the issue of group privacy or, as coined by Bloustein (1976) the "right to huddle". While legal provisions typically only protect the privacy of the individual as a natural person, there are still privacy risks associated with opening data in which groups of people can be identified (Floridi 2014). The issue of group privacy is also being discussed in the field of web advertising, where there is a proposal to substitute cookies, which can be used to identify a unique person, with Federated Learning of Cohorts (FLoC), which should only allow for the identification of "interest cohorts" (Dutton 2021). Critics point to the fact that even if individual profiling within a cohort is not possible, FLoC can allow for discrimination of certain groups: "a targeting system may be used to decide who gets to see job postings or loan offers just as easily as it is to advertise shoes" (Cyphers 2021). This concern is similar to the idea of social sorting defined by Lyon (2005) and is highly relevant in the field of OGD as the data being released by government could be used to discriminate against vulnerable groups of people.

Borgesius et al. (2015) identifies chilling effects as another threat associated with opening data. Chilling effects occur when citizens refrain from accessing a certain service because they fear the public office will store and share their data with others, which is a particularly sensitive issue for people who are at risk of being targeted by immigration agencies (Borgesius et al. 2015). Finally, open data may lead to misleading interpretations and analyses, especially when it is not accompanied by appropriate documentation (Zuiderwijk and Janssen 2014).

3.2.3 Barriers

Civil servants play a key role in the release of OGD and are involved in deciding which data is suitable for publishing and in making the actual decision to release it (Crusoe and Melin 2018).

Through interviews and workshops with a number of civil servants, Janssen et al. (2012) identified barriers affecting civil servants in the process of opening data. Organisations tied to political offices tended to have a risk-averse culture, which impeded the release of data. A significant barrier was the worry that some of this data might be damaging to the very institution that published it and thus, even when disclosing it, the hope was it would never be found or used by the public (Janssen et al. 2012).

In a systematic review of the literature, Crusoe and Melin (2018) found that barriers to OGD generally tend to have either a technical, organisational or legal nature. Crusoe and Melin (2018) identify five processes affected by these barriers: identifying which datasets are "suitable" for release, deciding whether or not to make them public, publishing, the use of the data by a third-party and, finally, measuring the impact generated by the release of data. Decision-makers need to confront these decisions and processes but operate with bounded rationality (Luthfi et al. 2020). This means that the capabilities and information available to decision-makers are not perfect and the use of heuristics is needed in order to make decisions quickly and with a reasonable cognitive effort (Luthfi et al. 2020; Gigerenzer and Selten 2002). Moreover, decisions on whether to open data are confronted with risk aversion and lack of clarity over the priorities and objectives that should guide the release of data (Luthfi et al. 2020). Understaffing can also play a signficicant role, especially when considering that some requests for data require a thorough analysis, as the answer might not be straightforward and policies need interpretation (Luthfi et al. 2020).

Crusoe and Melin (2018) identify further intra-organisational barriers related to the consequences of opening datasets, such as:

- Laws and regulations blocking the publishing
- The safety of third-parties described by the datasets
- Liability in the case of damages caused by the release of data

- Privacy violations and the loss of value that is sometimes caused by anonymisation

The release of data is also influenced by civil servants' perceptions and beliefs. According to Ubaldi (2013):

> The belief that making data public disempowers public officials, or makes them more vulnerable as they risk unveiling faults, can at times create an environment among civil servants, or even policy makers, which does not fully support implementation of OGD initiatives.

In other words, releasing data might lead to more questions and inquiries about the work and decisions of the very same people that are opening data.

Wirtz et al. (2016) found "five perceived barriers (perceived legal barrier, perceived bureaucratic decision barrier, perceived organizational transparency, perceived hierarchical barrier and perceived risk-related attitude of administrative employees)", all of which act as a constraint to open data initiatives.

Given the complex challenges, biases and misperceptions facing civil servants involved in decision-making about open data, there is a need for training tools to facilitate learning about the topic. Still, organising training sessions in government has its own set of challenges. Carrel (2000) identifies several myths and obstacles associated with the delivery of training in governmental organisations. There is an expectation of immediate results to be used practically in day to day activities, an expectation is difficult to meet for training programmes in a governmental setting. Another barrier is sometimes constituted by public opinion and press coverage. A simulation or training exercise, for example, may find that the organisation was unprepared for a certain situation, which is usually the very point of the exercise. The negative media coverage and public opinion that originates might deter organisations from participating in future training activities. There is also a preference to rely on internal resources and expertise which might limit learning opportunities, especially around challenges requiring international expertise. Finally, in describing the attitudes towards training in governmental organisations in Switzerland, Carrel (2000) highlights a certain reluctance which can be synthesised as *"No time - No need - No Money* (Carrel 2000). In other words, time allocation is a constant complaint from officials and training solutions should be delivered in short sessions.

In order to address these myths and challenges, the following section will introduce the concepts of serious game and collaborative learning, which offer possible solutions to the need for training.

3.3 Serious games and games for government

Serious games are being used in schools, universities and professional settings to teach subjects like foreign languages and mathematics, but also to simulate and train for complex scenarios like business management or management of logistics and manufacturing (Gloria et al. 2014). Unlike commercial or arcade video games, the main purpose of a serious game is something other than pure entertainment (Michael and Chen, 2005, as cited in Laamarti et al., 2014). According to Djaouti et al. (2011), the first use of the term "serious games" in its contemporary meaning can probably by attributed to Abt (1970):

> Games may be played seriously or casually. We are concerned with serious games in the sense that these games have an explicit and carefully thought-out educational purpose and are not intended to be played primarily for amusement. This does not mean that serious games are not, or should not be, entertaining (Abt, 1970, as cited in Djaouti et al., 2011).

As shown in figure 1, serious games are composed of experience, multimedia and entertainment (Laamarti et al. 2014). Compared to serious games, computer games only have the entertainment and multimedia components, and are lacking the "environment which delivers a content emanating from a know-how or experience" (Laamarti et al. 2014).

The project "A Collaborative Classification of Serious Games" (Alvarez and Djauti 2006) collected and classified 3400 serious games according to criteria such as the core rules, purpose and target audience. Numerous serious games borrow game mechanics that are successfully used in arcade games in order to create a new educational experience. Socrates Jones (Fallon and Reznitskaya 2013), for example, is inspired by and uses the same mechanics found in Ace Attorney. Ace Attorney is an entertainment game which puts the player in the shoes of a young and inexperienced attorney, cross-examining witness testimony and presenting evidence. The game is set in a court-room and in some parts it roughly resembles court-proceedings. Socrates Jones uses the same mechanics as Ace Attorney (they are both visual novels), but is considered “serious” because it was created with the main purpose of educating players about philosophical concepts such as critical thinking (**?**). Socrates Jones achieves this by encapsulating educational content inside a format that the player already knows.

Several serious games have been designed on the topic of open data; the list that follows has already been published in Di Staso et al. (a,b). Datascape (Wolff et al. 2017) sees players interacting with a map divided into squares, each containing different features like houses, farms and lakes. Players are presented with questions such as *"Where would*

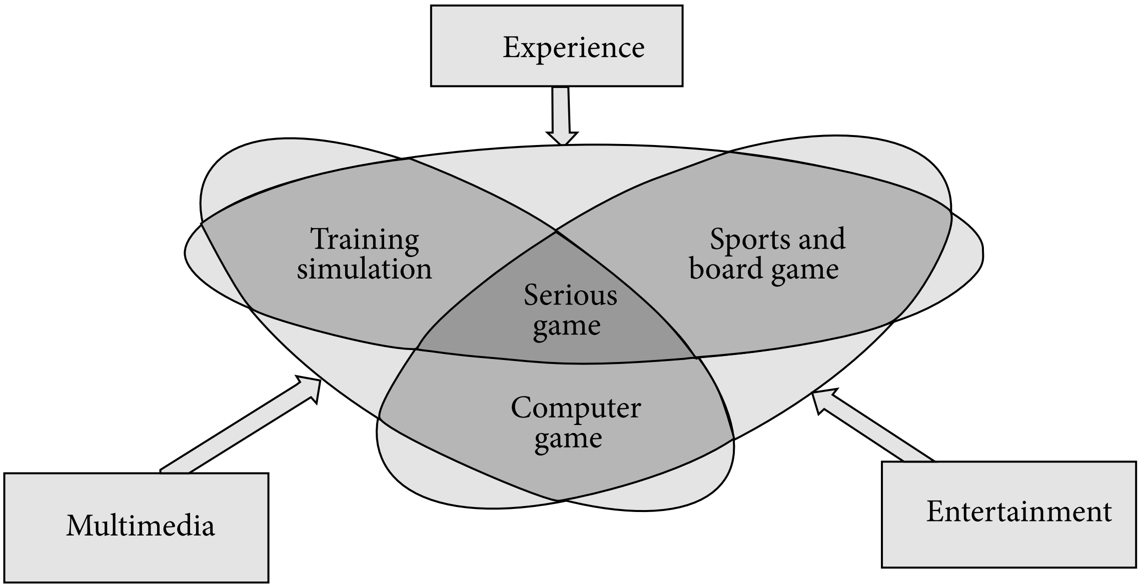

Figure 1 Definition of serious games. Reprinted from Laamarti, F., Eid, M., and El Saddik, A. 2014. "An Overview of Serious Games," *International Journal of Computer Games Technology* (2014), p. 358,152. Copyright 2014 Fedwa Laamarti et al.

you site a windfarm?" and need to query the map for data that can help answer the question. Datopolis (Broad and Tennison 2015) is a board game from the Open Data Institute. Players have data tiles, (i.e. "geospatial", "weather") which can be laid on the board as either open or closed. A player can use their own closed data or other players' open data to build tools like mobile apps or research projects. Throughout the game, players need to negotiate with each other in order to get the data they need for their tools. The Open data card game (Goraya 2015) is about how datasets can be combined into useful applications. Players are divided into groups and are given three cards representing datasets and have an empty canvas with prompts to write about possible ideas for turning the them into something valuable. Data Dealer (Averintsev et al. 2012) is an online video game dealing with the often shady business of data brokers. While the game does not specifically address OGD, it does shed a light on how combining datasets from different sources with personal information can lead to problematic outcomes. The objective of the game is to buy datasets from questionable or corrupt individuals and resell the data to private firms like insurance or housing companies.

Winning Data Kleiman et al. (2019) is a in-person game for 4 players which simulates the environment of a public office tasked with processing citizens' demands and deciding whether or not to open certain datasets. Participants play in the roles of citizen, civil servant, colleague, and boss. Each of the four rounds of the game is divided in data processing and data labelling. During the data processing (shown in figure 2), the civil servant needs to process citizen demands' according to a routine, which usually involves asking the other players, who are sitting in front of individual desks, to throw dice and write down the resulting number on different pieces of paper. During the data labelling, the civil servant, colleague and, at their discretion, also the citizen need to discuss whether or not to open the datasets that they processed in the previous phase. Crucially, in a one group pre-test post-test quasi-experiment, the game was found to be helping civil servants to "develop a more realistic perspective of opening governmental data" and "increase participants' awareness of elements of risk for public data provision, both regarding individual privacy and institutional security" (Kleiman et al. 2020).

Figure 2 A game session of Winning Data. Reprinted from Kleiman, F., Janssen, M., Meijer, S., and Jansen, S. J. 2020. Changing Civil Servants' Behaviour Concerning the Opening of Governmental Data: Evaluating the Effect of a Game by Comparing Civil Servants' Intentions before and after a Game Intervention, *International Review of Administrative Sciences.* Copyright 2020 Kleiman et al.

Given the evidence in support of the efficacy of Winning Data as a tool to teach about open data, this game was chosen as a basis to develop a new digital (remote) serious game with the same objectives.

3.4 Collaborative learning

Just because a game allows multiple people to play at the same time or in a shared environment, it cannot be automatically classified as collaborative. In fact, even games that make use of cooperative mechanisms can fail to deliver a collaborative experience (Zagal et al. 2006). Within the realm of multiplayer games, Zagal et al. (2006) identify three categories: competitive, cooperative and collaborative games. Competitive games put the players against each other in a competition. Monopoly is one example of such game, where players need to accumulate money and properties at the expense of each other. While Monopoly has some cooperative features, for example property trading, which allows two or more players might decide to coordinate at the expense of someone else, it is still a largely competitive game.

The third category identified in Zagal et al. (2006) is the one of collaborative games where players form a team and succeed or fail together. A successful collaborative game should create a tension between individual and group goals by setting diverging incentives and rewards (Zagal et al. 2006). Wendel et al. (2013) found that a collaborative serious game designed following the criteria from Zagal et al. (2006) was well received, with teams able to complete collective tasks and having fun in the process.

Dillenbourg (1999) notes that there are three dimensions required to define collaborative learning: (1) the scale (both in term of group size and time span), (2) the meaning of learning and (3) the meaning of collaboration. On the first end of the spectrum are activities where time, group size, and the intensity of learning and collaboration are limited. On other end of the spectrum are activities with very large groups that happen over lifetime and where learning is profound and collaboration intense. Collaborative learning is not method but rather a "*situation* in which particular forms of interaction among people are expected to occur, which would trigger learning mechanisms, but there is no guarantee that the expected interactions will actually occur" (Dillenbourg 1999). In fact, the composition of the group or environmental factors might impede collaboration. To illustrate this point, Davis et al. (2018) conducted an experiment with multiplayer video games and children aged 11-13 years. Findings indicate that initial conditions had a significant impact on group collaboration. Prior social ties among some of the players was found to be one the most relevant impediments to collaboration for all groups analysed; players who knew each other beforehand would usually just interact among each other and disconnect from the rest of the group.

Serious games have are powerful tool to elicit collaboration and knowledge sharing within a certain group. Agogué et al. (2015) found that a role-playing serious game was able to eleicit "rich collective knowledge sharing" and that "the two main components of a Serious Game, i.e., immersion through role-playing and simulating reality, enabled a collective capability to differently investigate an issue already known within the firm" (Agogué et al. 2015).

Collaborative learning can take a number of different shapes. Participation can happen in person in a completely analogue fashion, as well as with the aid of digital tools such as projectors or companion apps running on a smartphone or laptop. When collaborative learning becomes digital it can still happen in person with local multiplayer games or remotely with games relying on online servers and sometimes voice chat features.

In the earliest phases of this research, the project was envisioned as the creation of a companion app for Winning Data (Kleiman et al. 2019), which would still require in-person facilitation and gameplay while streamlining some game mechanics through a digital artefact. However, just a few weeks after the beginning of this project, the World Health Organisation declared COVID-19 a pandemic and lockdowns began all over the world. Consequently the aim of the project became to develop an entirely digital version of Winning Data, which could be played remotely. As Kriz (2020) puts it:

> As a professor using several of these kinds of games in the curriculum it is difficult and sometimes impossible to create equal learning processes with games over distance learning. I am also involved in translating one of my own business games (a hybrid game that uses computer simulation, role-play and a board game with several haptic and analog elements) into a purely web-based and distance learning tool. It is not only difficult to change physical game elements into digital game elements but also, as our experience shows, the original game cannot be translated in all aspects and the new game cannot meet all of the same learning objectives (and on a personal note, the new game is less enjoyable for me as a facilitator) (Kriz 2020, p. 404).

Inevitably, translating Winning Data into an online experience encountered similar challenges, as it was hard to accurately recreate all aspects of the game within the limitations of online participation.

3.5 Summary

The first section of this chapter presented the concept of OGD, along with its applications and benefits but also its "dark side" (Zuiderwijk and Janssen 2014). OGD was found to be an important tool to enable transparency in government. In fact, citizens and journalists can access datasets to interpret data and investigate social issues. OGD also open the door to the production of useful tools for citizens; examples were presented showing applications created by private individuals that filled the gaps of digital public services by leveraging open data. At the same time, the opening of datasets can lead to unintended consequences. For example, open datasets can be combined with other present or future datasets to identify individuals. OGD can also have negative effects on vulnerable groups, which might refrain from interacting with governmental services if they fear that this will lead their data being released. The issue of group privacy was presented: even when individuals are not identifiable, people might demand privacy as a group in order to avoid social sorting and discrimination. Next, barriers affecting data release by civil servants were presented, including real or perceived risks regarding the infringement of laws and regulations, liabilities and the fear of violating privacy. Given the challenges of OGD decision-making and the need to overcome these barriers, the concepts of serious games and collaborative learning were introduced as a possible solution to the need for training about open data in the public sector. A definition of serious games was found in the literature and several examples of serious games on the topic of open data were presented. Collaborative learning was found to be a powerful element for serious games. At the same time, collaboration is situational and can only be encouraged by the design of the experience, but not guaranteed. Groups of players might decide to compete with each other or cooperate, rather than collaborate.

4 Research methodology

4.1 Introduction

This chapter will present the methodologies used to answer the questions introduced in Chapter 2. The methodology used to guide the game development will be introduced, starting with a review of the fundamental features to be kept from Winning Data. Game mechanics and learning mechanics to be implemented in the game will also be listed and mapped. The chapter will continue to explain the methodology used to assess the learning outcomes and the research procedure used to collect data.

4.2 Game development

After reviewing Winning Data, its game assets and rules and facilitating an actual game session, the requirements that should guide the development of the digital version of the game were listed. The list that follows has already been presented in Di Staso et al. (a,b):

- The game must be playable in 30-40m in order to allow for the entire experience to last no more than one hour.
- The setting of the game must be a public office
- The aim of the game must be to process files coming from the citizen and decide whether to disclose data that is generated in this process
- Players must receive a reward only after processing the files and correctly labelling the associated dataset

Following the approach used by Wendel et al. (2013), game development was guided by the principles proposed by Dillenbourg (1999), so as to increase the chances of collaborative learning actually occurring:

(1) Initial conditions. These include everything concerning the arrangement of the physical - or virtual - space and the group composition and size.

(2) Role-playing. The reasoning behind role-playing is that by requiring a combination of different skills and capacities assigned to the players, the game can encourage collaboration.

(3) Integrated rules. These rules concern the the design and behaviour of the interface - be it physical or virtual - that they players are presented with.

(4) Facilitation. A good game facilitator is not intrusive but rather intervenes as required to ensure a smoother gameplay and can indeed encourage collaboration by nudging players in the right direction.

In order to guide the game design and develpment process, the LM-GM framework by Arnab et al. (2015) was used. This framework proposes two set of building blocks to analyse a given serious game - learning mechanics and game mechanics (figure 3). In order to apply this model during game design - as outlined in Arnab et al. (2015) - it is necessary to:

(1) Identify the game and learning mechanics that are going to be used throughout the game

(2) Establish the relationships between them and describe their usage and implementation

(3) Build map showing how their used in the flow of the game

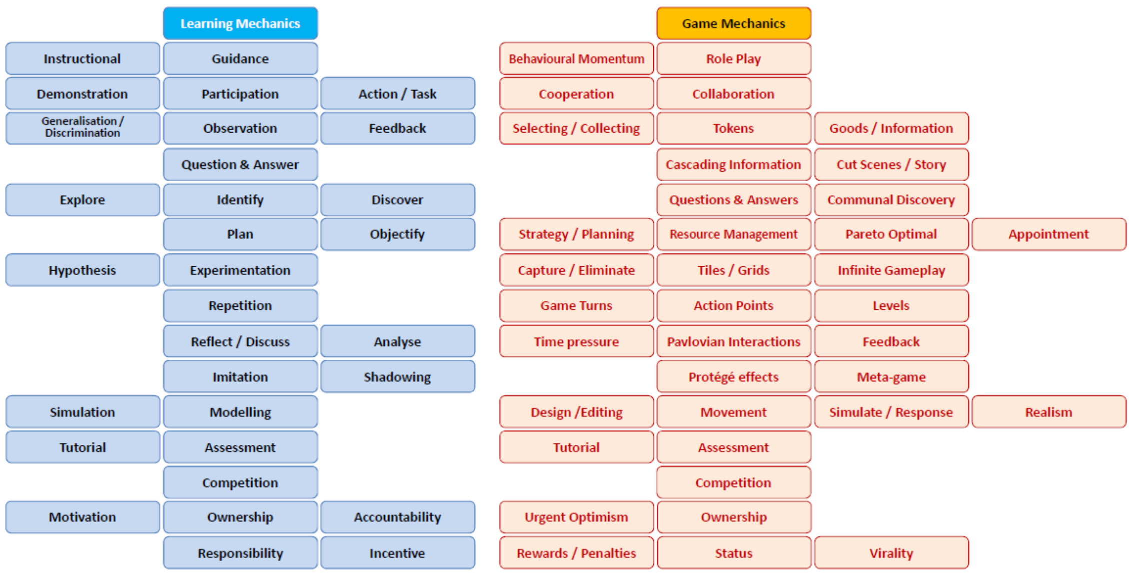

Figure 3 Non-exhaustive list of mechanics for serious games in the LM-GM model. Reprinted from Arnab, S., Lim, T., Carvalho, M. B., Bellotti, F., de Freitas, S., Louchart, S., Suttie, N., Berta, R., and De Gloria, A. 2015. Mapping Learning and Game Mechanics for Serious Games Analysis, *British Journal of Educational Technology* (46:2), p. 395. Copyright 2014 British Educational Research Association

Starting from an analysis of Winning Data (Kleiman et al. 2019) and from the game mechanics listed in figure 3, the LM-GM analysis was conducted, in order to identify the main game and learning mechanics and guide the development process for Data Belt (table 1). Note that some game mechanics, namely the *random-role assignment*, *asymmetric* *decision-making* and *rounds* mechanics, were not present in the original list by Arnab et al. (2015).

GM	LM	Implementation	Usage
Tutorial	Instructional	Plan; Live presentation with slides and videos	To explain how the game and its interface works
Random role-assignment; Rounds; Time pressure;	Plan; Repetition	Players shuffled randomly into roles, a player never plays in the same role twice. Time available becomes shorter each round.	Players need to plan their actions together based on their roles. In subsequent rounds, players explain to each other how to play their previous role. Challenge becomes harder each round.
Collaboration; Role play;	Action/Task; Guidance	Real-time collaborative tasks. Skills and responsibilities specific to each role. Facilitator guides the process as necessary	Creates positive interdependence and relates to the public office environment. The groups get to practice collaboration before discussion.
Feedback; Rewards & Penalties	Assessment; Accountability; Reflect and Discuss; Incentive	Summary screens showing each players' actions/decisions in the past round. Collective score for the team.	Encourages collaboration. Players take responsibility if they make a decision against the team's advice, encouraging consensus.
Questions & Answers	Reflect and Discuss	Synchronised selection screens. Time allocated for debate/discussion.	Encourages discussion and consensus vs individual decisions.
Asymmetric decision-making	Simulation	One role has more decision-making power but less information than the others.	Simulates real issues in decision-making processes.

Table 1 LM-GM analysis for Data Belt

As shown in table 1, it was decided that instructions on how to play the game (the *tutorial*) would be delivered using a live presentation with slides given by the facilitator. While not a definitive solution, this was deemed the most efficient one, as opposed to a tutorial mode integrated in the the game, which would have required extensive development, debugging and user-testing activities. Another set of game mechanics is constituted by *random-role assignment*, *rounds* and *time pressure*. Since the initial conditions play a significant role in how players will collaborate throughout the game session, the random-role assignment can help avoid the bias caused by players being able to choose their own game roles.

Therefore, in every round of the game, players are shown what role they are assigned to and have as much as they want to make plans and prepare for the incoming round. The planning phase is also important because in this moment players can coach each other on how to play a certain role, thereby fostering communication and collaboration within the group. The division of the game in *rounds* allows for some degree of repetition. The decision to have game rounds which, unlike *levels*, are essentially identical to each other was made because the game was already "hard enough" and introducing more variety and changing scenarios would have probably created too much complexity. Instead, it was decided to only use *time pressure* as required to keep the game challenging throughout the entire session. The game mechanics of *collaboration* and *role play* were used to foster learning through a group task and to get the team to work together before engaging in a discussion. Positive interdependence, real-time collaborative tasks and facilitator guidance were aimed at having every player make a contribution to the team's effort and avoid leaving some players behind and disengaged. This is especially important to maximise the chance that all players participate in the discussion on opening data. *Feedback* and *rewards & penalties* were chosen as one of the main mechanisms to incentivise players to improve their performance from one round to the next. A collective score and screens detailing the decisions taken by each player can also serve an incentive to reach a consensus among the group. Finally, *asymmetric decision-making* was chosen as the appropriate game mechanic to simulate the hierarchical structure of the decision-making process in public offices.

Following the second step in the framework by Arnab et al. (2015), a game map was built, in order to show the connection and flow connecting game and learning mechanics (figure 4). There are two main things to be noted in the arrangement of the game and learning mechanics: (1) each round has a fast-paced section (*collaboration* and *time pressure* which - after *feedback* - is followed by a slower section for *questions & answers* and *reflect and discuss*. The game alternates between a "fun" part and a more deliberate and intensive part dedicating to reasoning and discussing open data.

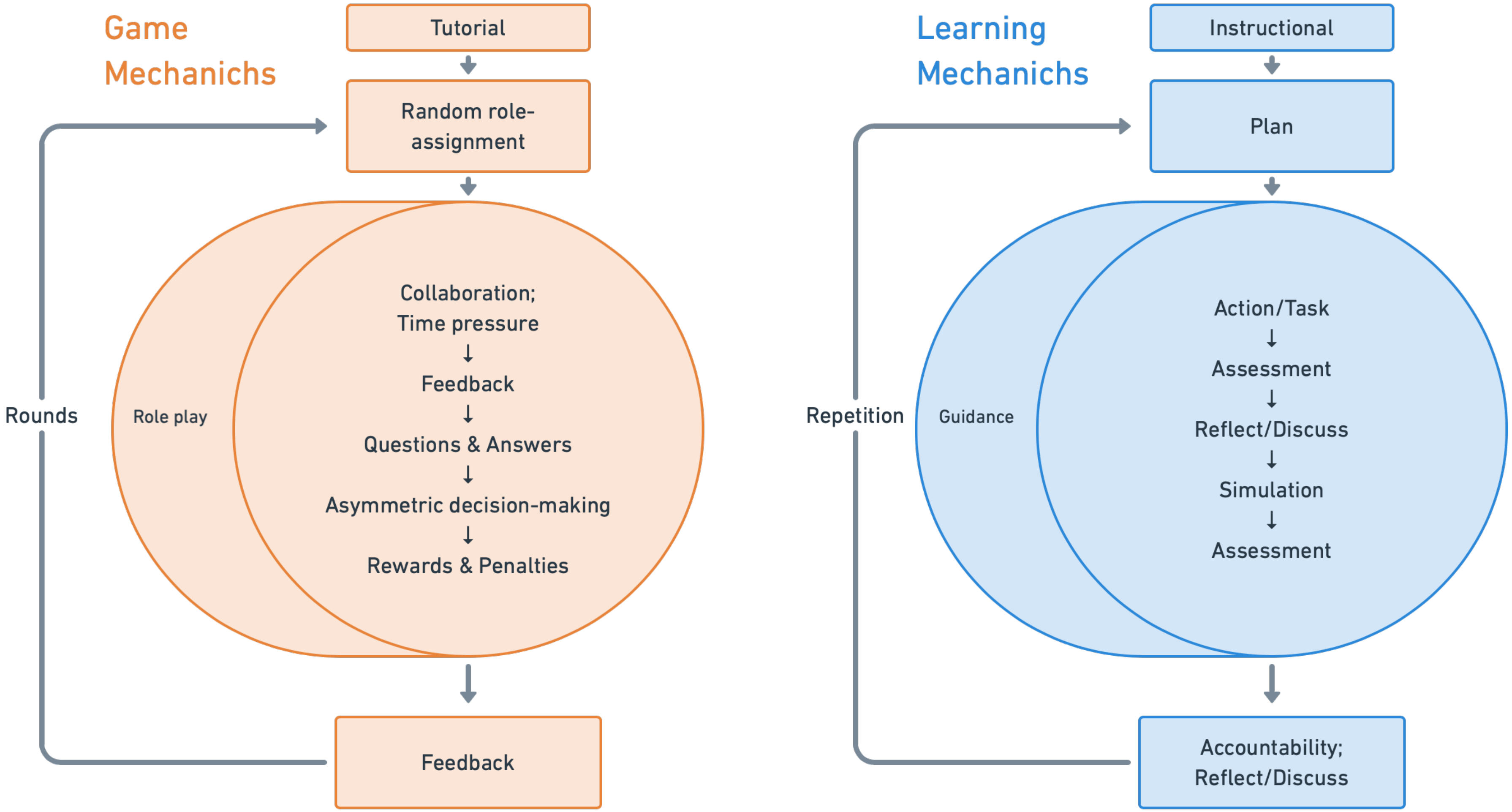

Figure 4 Game map for the design of Data Belt, drawn following the framework in Arnab et al. (2015)

4.3 Quasi-experiment

In order to test the learning outcomes, a one group pre-test post-test quasi-experimental design was chosen (Campbell 1963). This methodology and the surveys used in this research are similar to Kleiman et al. (2019), with the main difference being that the game sessions happened in an online setting, instead of in person. The surveys used for this research are identical in content to the ones used in Kleiman et al. (2019) and were adapted to the online environment.

Other than in Kleiman et al. (2019), the one group pre-test post-test quasi-experimental design has already been used to evaluate serious games for health education (Hong et al. 2020). However, especially in the context of evaluating training or educational interventions related to health, this method has received significant criticism (Young et al. 2020; Knapp 2016). In fact, in a one group pre-test post-test quasi-experiment there are a number of uncontrolled variables, as listed by Campbell (1963):

- History, meaning external events that occur between the pre-test and post-test that are unrelated to the experience
- Maturation, which is the change in psychological state that is inevitable as time goes on. Participants might simply be in a different moods when filling the pre-test and post-test.
- Testing, which includes variables such as participants becoming aware of the objectives of the research upon filling the post-test survey.
- Instrumentation, refers to distortions caused by the same measuring instrument being used multiple times. In the context of the evaluation of educational content, this might refer to human observers, who may become better at their jobs as they perform more observations.
- Statistical regression, is a variable which comes into play when non-random samples are used. If a sample was selected because of low performance on a certain metric "they have no other way to go than up, so to speak" Knapp (2016).
- Mortality, which is the bias caused by participants dropping out of the experiment.

Due the lack of control over these variables, the one group pre-test post-test quasi-experimental design can only be considered pre-experimental given its weaknesses (Campbell 1963).

As illustrated by the flowchart in figure 5 the experiment was conducted as follows:

(1) A participant volunteers for the experiment

(2) When enough participants are found, a game session is scheduled

(3) An email is sent to all participants with the technical requirements for the game (a phone and a laptop with a browser and an internet connection)

(4) At the scheduled time, the video call starts

(5) The facilitator and participants introduce themselves and the facilitator gives a 10 minute tutorial about how to play the game

(6) Participants play Data Belt

(7) When the game ends, a post-test survey is distributed

(8) After all participants completed the post-test survey, the group is asked to provide their thoughts and impressions about the game (debrief)

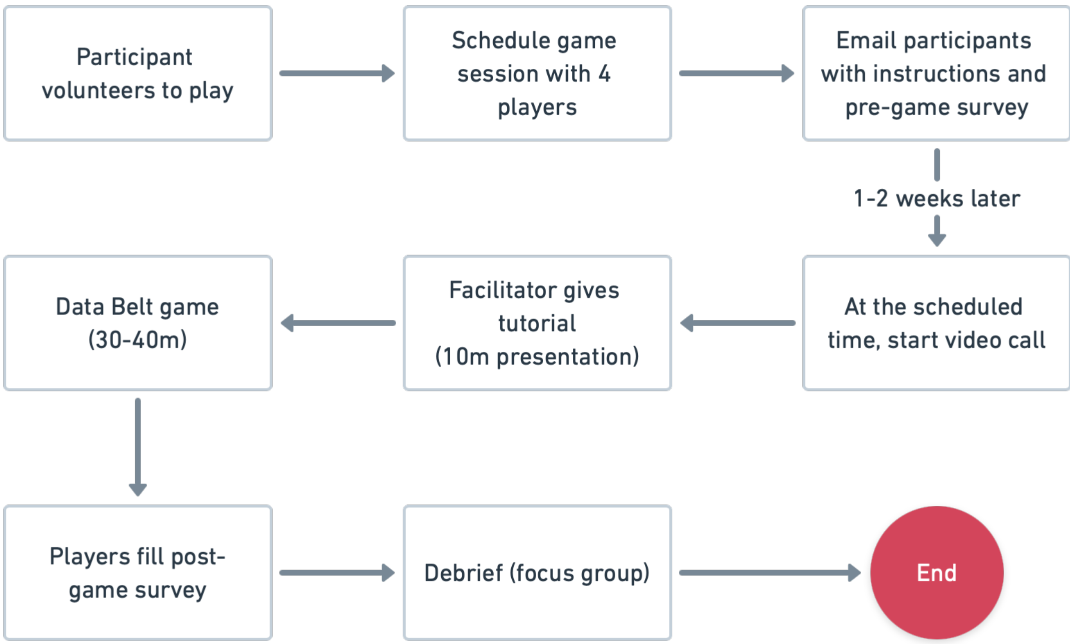

Figure 5 Flowchart illustrating the research procedure

4.4 Debriefing

The debriefing done for educational game sessions should be tailored to the audience, purpose of the game and receiver of the learning outcomes (Peters et al. 1997). Using the criteria defined by Peters et al. (1997), Data Belt was classified as an open simulation where the participants and facilitator are the addressees of the learning outcomes.

While Data Belt differs from what is classically considered an open-world simulation in game literature, it can still be classified as an open simulation, given that: (1) the game allows for emergent gameplay, (2) it was explained to participants that there are no "right" answers on whether or not to open datasets, rather, the objective is to simply have participants discuss the issue. Therefore, Data Belt is compatible with the category of games for education and development, since "neither the game designers nor the debriefers have specific ideas about how participants should act or which courses of action are best" Peters et al. (1997).

Crookall (2010) argues that debriefing is absolutely central to the learning experience: "for all their wonderful creativity and enthusiasm, some serious and other gamers seem to have forgotten that the learning comes from the debriefing, not from the game" (Crookall 2010). Lederman (1992), citing Pearson and Smith (1985), traces the origin of debriefings from military exercises, in which debriefings were used to reconstruct what happened and think about new insights from the experience that just occurred. Overall, Lederman (1992) identifies three fields in which debriefs are commonly used:

- In the military context, debriefs are done at the end of operations or exercises or even after a hostage release, to gather information.
- In psychology, debriefs are used at the end of an experiment to remove the deception and tell the participants about the real aim and purpose of the experiment.
- In education, debriefs can help the teacher of facilitator assess what has been learned - if anything - and why.

In summary, debriefs provide useful insights to both debriefers and teachers into what did or did not work during the learning experience Lederman (1992). They are also an occasion for debriefers to share insights with each other and can meaningfully contribute to more meaningful and longer-lasting learning Crookall (2010). Crookall et al. (1986) argues that debriefs, in fact, are at the very centre of the learning experience of serious games.

4.5 Summary

This chapter presented the methodology and requirements used to transform the in-person game Winning Data into an online experience. A list of requirements was drafted and development was guided by principles of collaborative learning found in the literature. Game mechanics, learning mechanics and their implementation and usage in the new game were mapped. In order to test the learning outcomes of Data Belt, the one group pre-test post-test quasi-experimental design was chosen and its limitations were listed. The research procedure also includes a short debrief, in line with the recommendations from the literature on game-based learning.

5 Results

5.1 Introduction

This chapter starts by describing the game prototype used to conduct this research. The gameplay is explained, along with a comparison to the in-person game and a description of the adaptations that had to be made in order to bring the experience into an online setting. The chapter will proceed by comparing the Likert scores in the pre-test and post-test surveys in order to assess the learning outcomes. Finally, the results of the satisfaction section of the post-test questionnaire will be presented in order to measure acceptance of the game and self-reported learning goals.

5.2 Game prototype

A description of the game prototype has already been presented in Di Staso et al. (a,b).

Figure 6 Screenshots illustrating the game as seen by the four players during the data processing phase. Reprinted from Di Staso, D., Kleiman, F., Crompvoets, J., and Janssen, M. (s.d.)a. "Changing Civil Servants' Awareness about Open Data Using a Collaborative Digital Game," in *DG.O2021: The 22nd Annual International Conference on Digital Government Research*, Omaha, NE, USA, [In Press]

Data Belt is a real-time multiplayer game which needs 4 people to play together. During the 4 rounds of the game, players rotate between the roles of civil servant, citizen, and colleague. At the beginning of each round, players are presented with a description of the role and, when ready proceed to the data processing. In this phase, the citizen is presented with 5 empty files that need to be retrieved by the civil servant and colleague, signed, stamped, and delivered back to the citizen. The civil servant has the ability to apply stamps and send files back to the citizen, whereas the colleague can only apply signatures. The civil servant and colleague can both retrieve a file by entering its code onto a keypad. The most efficiency way to process a file is the following: (1) the citizen reads the file's code out loud, (2) the colleague enters the code into the keypad, retrieves it and signs it, then reads the code out loud, (3) the civil servant retrieves the file, stamps it and sends it back to the citizen. This order of events is not forced onto the players, which may choose, for example, to have the civil servant apply the stamps before the colleague can apply the signature, even though it would take more time. During the data processing, the boss monitors the remaining available time (represented by a calendar) and participates in a fictional "press conference" by tapping on the green question marks that appear on the screen to answer questions.

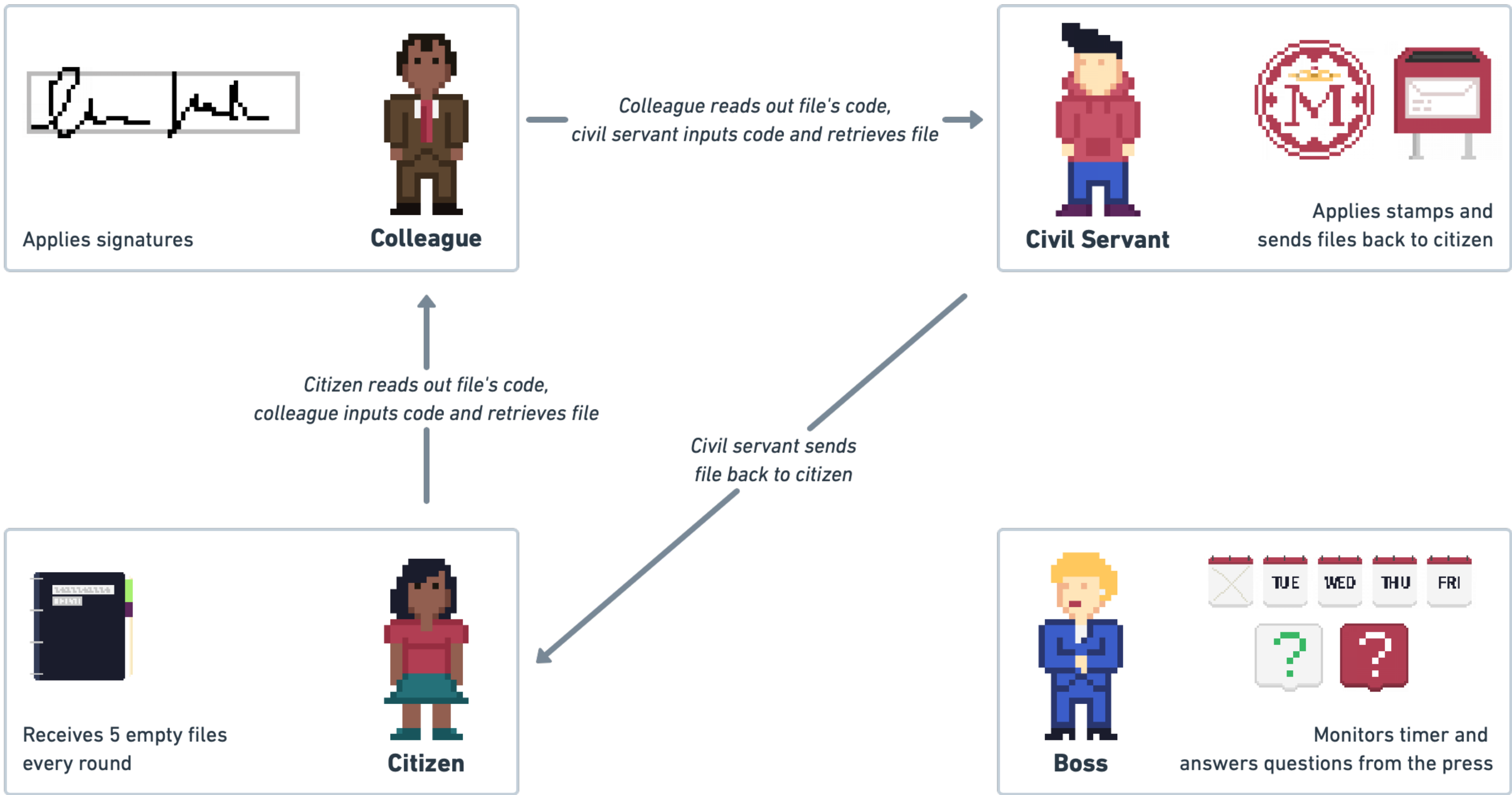

Figure 7 Map of Data Belt's roles and flow

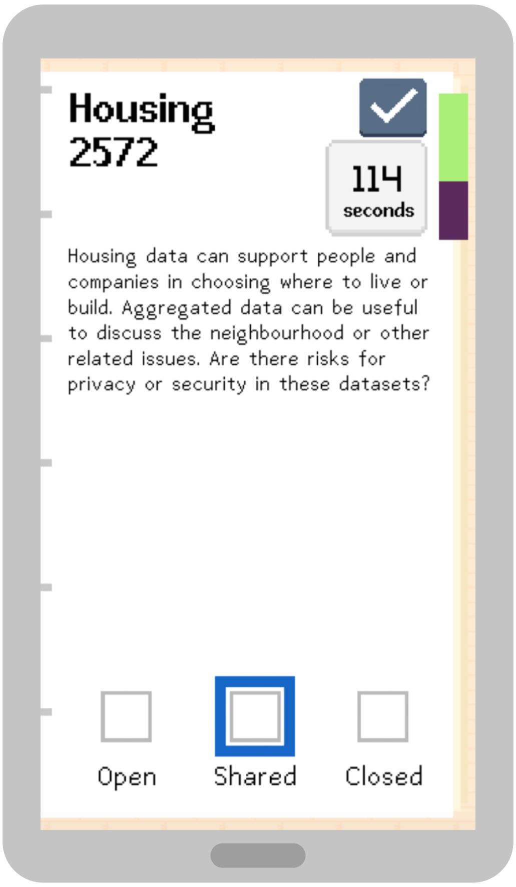

Figure 8 Dataset labelling selection, the blue square indicating the selection is synchronised across the screens of the citizen, civil servant and colleague. Reprinted from Di Staso, D., Kleiman, F., Crompvoets, J., and Janssen, M. (s.d.)a. "Changing Civil Servants' Awareness about Open Data Using a Collaborative Digital Game," in *DG.O2021: The 22nd Annual International Conference on Digital Government Research*, Omaha, NE, USA, [In Press]

At the end of the timer, or when all files have been processed, the data labelling phase begins. For each file that has been correctly processed a new dataset is generated with an associated description. The citizen, civil servant and colleague need to suggest to which degree the dataset should be disclosed, if at all. The three players, all synchronised on the same screen, read the content of the dataset and can suggest to open it completely as it is ("Open"), anonymise it by removing sensitive information and then share it ("Share") or keep it completely private ("Closed"). The selection made by any single player gets synchronised in real time across all devices, similarly to what happens in a collaborative document, in order to encourage players to reach a consensus among themselves. Once the citizen, civil servant and colleague have suggested a label for all datasets, these are transferred to the boss, who can see the suggestion and take a final decision.

Compared to Winning Data Kleiman et al. (2019), Data Belt has several key differences.

The way in which datasets are processed had to be redesigned so that the online experience could work. In Winning Data, the citizen and colleague are sitting at their desks and the civil servant walks to them, asks them to help process the dataset by throwing the dice and transcribing information. In the remote setting, players cannot walk to each other or throw dice, so the game works by giving the civil servant and colleague the ability retrieve datasets by inserting their unique code. Instead of throwing dice, players put stamps or signatures.

The second main transformation is about the data labelling. In Winning Data, the citizen, civil servant and colleague can discuss how to label a dataset while being in close proximity, with one player in charge of transcribing the decision. In the remote setting, players are less inclined to discuss among each other, especially if only one player is tasked with transcribing the resulting decision. Therefore, in Data Belt, the labelling choice is synchronised across the three plauers' screens and any one of them can change it in real time, thus making the task feel collective.

In Winning Data, unprocessed datasets are brought forward to the next round, giving more chances to the team to process and label them. In Data Belt, unprocessed datasets are simply discarded. This difference is due time constraints of the online interaction. The overall experience was kept as short as possible due to the fatigue caused by video calls and due to the higher office workload during the pandemic.

The consequences for incorrectly labelling datasets differ between the in-person game and the digital one. In Winning Data, not releasing enough data is punished with Freedom of Information (FOI) requests which put additional workload on the team and need to be processed immediately. On the other hand, if the team releases too much data (by labelling a dataset as open when it should have been closed, for example) the game enters a privacy crisis mode. Data Belt uses other, less evident penalties. When not enough data is released, the time available for data processing during the next round gets shortened (creating more pressure and workload for the team). When too much data is released for several datasets, the boss' press conference is disabled and the team loses the chance to score those additional points. This difference is due to the time and effort required to explain and understand complex game mechanics through a video call. The game was kept as simple as possible in order to shorten the tutorial and effort required to understand it.

Winning Data has different "routines" or procedures to process datasets which get harder as the game progresses. In Data Belt, all datasets are processed using the same procedure and, in order to keep the game challenging, the time available becomes shorter in the later rounds of the game. Again, this change was made in an effort to simplify the gameplay.

During the data labelling phase of Winning Data, the civil servant and colleague can choose whether or not to let the citizen participate in the decision. Instead, in Data Belt, the citizen always participates to the decision-making process. The decision to include the citizen in the data labelling was made based on Crusoe and Melin (2018) who argues that "inside a decision network, we find decisions to release processes. Participants are the organisation's internal management and enthusiasts, but also outsiders, such as activists, researchers, and politicians" (Crusoe and Melin 2018).

Zagal et al. (2006) looked at board games - which tend to have less complexity than electronic games - in order to extrapolate seven observations to guide the design of collaborative games. Following the methodology used in Wendel et al. (2013), the recommendations and their implementation in Data Belt are listed in table 2.

	Recommendation (Zagal et al. 2006)	**Implementation**
Lesson 1	To highlight problems of competitiveness, a collaborative game should introduce a tension between perceived individual utility and team utility.	The colleague and civil servant can simply focus on gathering the files on their screen in order to stamp or sign them, forgetting to help the rest of the team.
Lesson 2	To further highlight problems of competitiveness, individual players should be allowed to make decisions and take actions without the consent of the team.	In the dataset discussion, players can pick an option and skip ahead, but that would be very antisocial.
Lesson 3	Players must be able to trace payoffs back to their decisions.	The teams' decision about how to label the datasets is compared to the recommendation in the literature.
Lesson 4	To encourage team members to make selfless decisions, a collaborative game should bestow different abilities or responsibilities upon the players.	Each of the four roles available has specific skills (e.g. boss can see the remaining time, colleague can apply signatures).
Pitfall 1	To avoid the game degenerating into one player making the decisions for the team, collaborative games have to provide a sufficient rationale for collaboration.	When making a choice about whether or not to open a dataset, the selected option is synchronized for all players involved, and can be changed by any one of them.
Pitfall 2	For a game to be engaging, players need to care about the outcome and that outcome should have a satisfying result.	Players accumulate a score and the facilitator gives an indication of how good the score is based on the average.

	Recommendation (Zagal et al. 2006)	Implementation
Pitfall 3	For a collaborative game to be enjoyable multiple times, the experience needs to be different each time and the presented challenge needs to evolve.	*Not applicable, as the game was specifically designed to be played only once as part of a training session*

Table 2 Lessons and pitfalls from Zagal et al. (2006) applied to Data Belt

5.3 Quasi-experiment

A partial analysis of a subset of this dataset has already been presented in Di Staso et al. (b). From the pre-test survey it was found that a majority of players were male (19) and only a smaller fraction female (9). The average age was 41 years old. Regarding years of work experience in the public sector, the sample was heterogeneous: 0-5 years (12), 5-10 years (10), 15-20 years (1) and 20+ years (8). Most players worked for the federal (12) or provincial government (11) and a smaller fraction for other institutions (5). No players reported working for local or municipal government bodies.

Organisation	Country	Participants
Digicampus	Netherlands	12
Provincie Zuid-Holland	Netherlands	4
ICTU foundation	Netherlands	4
ENAP Innovation Week	Brazil	4
EU institutions	Various	4

Table 3 Summary of the participating organisations

The main analysis conducted on the pre-test and post-test surveys was a paired samples t-test, which is useful when there are two experimental conditions - in our case the *before* and *after* playing Data Belt - and the same set of participants experienced both of them (Field et al. 2012). The paired samples t-test offers a comparison of the means for two experimental conditions while taking into account the standard error of the differences (Field et al. 2012). The Likert scale goes from 1 (Strongly disagree) to 7 (Strongly agree).

			Pre-test		Post-test			
	Description	n	$\bar{x}$	σ	$\bar{x}$	σ	$\Delta\bar{x}$	p
lk_1	I produce public sector data in my work	28	4.25	2.07	4.29	1.78	0.04	0.93

	Description	n	Pre-test $\bar{x}$	Pre-test σ	Post-test $\bar{x}$	Post-test σ	$\Delta\bar{x}$	p
lk_2	Some public sector data can be shared	28	5.11	1.81	6.00	1.31	0.89	**0.01**
lk_3	I know how to make public sector data available for others to access	28	4.00	1.91	4.11	1.83	0.11	0.72
lk_4	People in my office know how to make public sector data available for others to access	28	4.61	2.04	4.61	1.62	0.00	1.00
lk_5	Public sector data that results from my work cannot be shared for privacy issues	28	3.36	1.59	2.93	1.36	-0.43	0.20
lk_6	Public sector data that results from my work cannot be shared for security issues	28	2.68	1.70	2.71	1.41	0.04	0.91
pe_1	Providing open public sector data improves citizen services	28	5.96	1.00	6.25	0.75	0.29	**0.02**
pe_2	Providing open public sector data improves policymaking processes	28	6.07	1.09	6.18	0.86	0.11	0.48
pe_3	Providing open public sector data creates trust in government	28	5.93	1.18	5.93	1.09	0.00	1.00
pe_4	Providing open public sector data promotes citizen participation	28	5.57	1.26	5.64	1.22	0.07	0.76
pe_5	Providing open public sector data increases transparency	28	6.39	0.83	6.18	1.02	-0.21	0.06
pe_6	Providing open public sector data is of benefit to me	28	5.21	1.64	5.25	1.76	0.04	0.91
pe_7	Providing open public sector data will help me doing my job	28	5.11	1.79	4.75	1.92	-0.36	0.21
pe_8	Providing open public sector data will increase my productivity	28	4.61	1.89	4.50	1.84	-0.11	0.67
pe_9	Providing open public sector data improves my performance in my job	28	4.75	1.97	4.54	1.75	-0.21	0.38
pe_10	Providing open public sector data has benefits which are difficult to explain	28	3.54	1.79	4.36	1.81	0.82	**0.01**
ee_1	I clearly understand how to provide open public sector data	28	3.68	1.66	4.14	1.90	0.46	0.08

	Description	n	Pre-test $\bar{x}$	Pre-test σ	Post-test $\bar{x}$	Post-test σ	$\Delta\bar{x}$	p
ee_2	Providing public sector data is a threat	28	2.07	0.94	2.79	1.47	0.71	**0.02**
ee_3	I fear individual privacy by providing public sector data	28	2.71	1.15	3.25	1.55	0.54	0.07
ee_5	I fear people will have false conclusions if public sector data is provided	28	3.36	1.68	3.21	1.50	-0.14	0.58
ee_6	Learning to provide open public sector data will be easy for me	28	4.50	1.43	4.86	1.51	0.36	0.30
si_1	People who are important to me think that I should provide open public sector data	28	3.64	1.57	3.75	1.46	0.11	0.65
si_2	License and legal frameworks make it difficult to provide public sector data	28	3.96	1.45	3.54	1.55	-0.43	**0.03**
si_3	Providing public sector data is not a priority for me	28	3.32	1.68	4.11	1.85	0.79	0.07
si_4	Providing public sector data is not a priority for the office I work for	28	3.21	1.79	3.75	1.99	0.54	0.23
si_5	I have the necessary autonomy to provide public sector data	28	2.54	1.43	3.21	1.55	0.68	**0.04**
si_6	My work does not require me to provide open public sector data	28	4.29	2.11	4.00	2.02	-0.29	0.44
si_7	My superiors expect me to provide open public sector data	28	3.18	1.87	3.46	1.86	0.29	0.41
si_8	I have assistance available concerning the provision of open public sector data	28	3.29	1.84	4.07	2.12	0.79	**0.03**
bi_1	I already provide open public sector data in my work	28	3.64	1.87	4.00	2.07	0.36	0.18
bi_2	I intend to provide open public sector data in the future	28	4.64	2.00	5.07	1.82	0.43	0.15
bi_3	I predict that I will provide open public sector data in the future	28	4.64	2.09	5.07	1.96	0.43	0.17

Table 4 Likert scores comparison

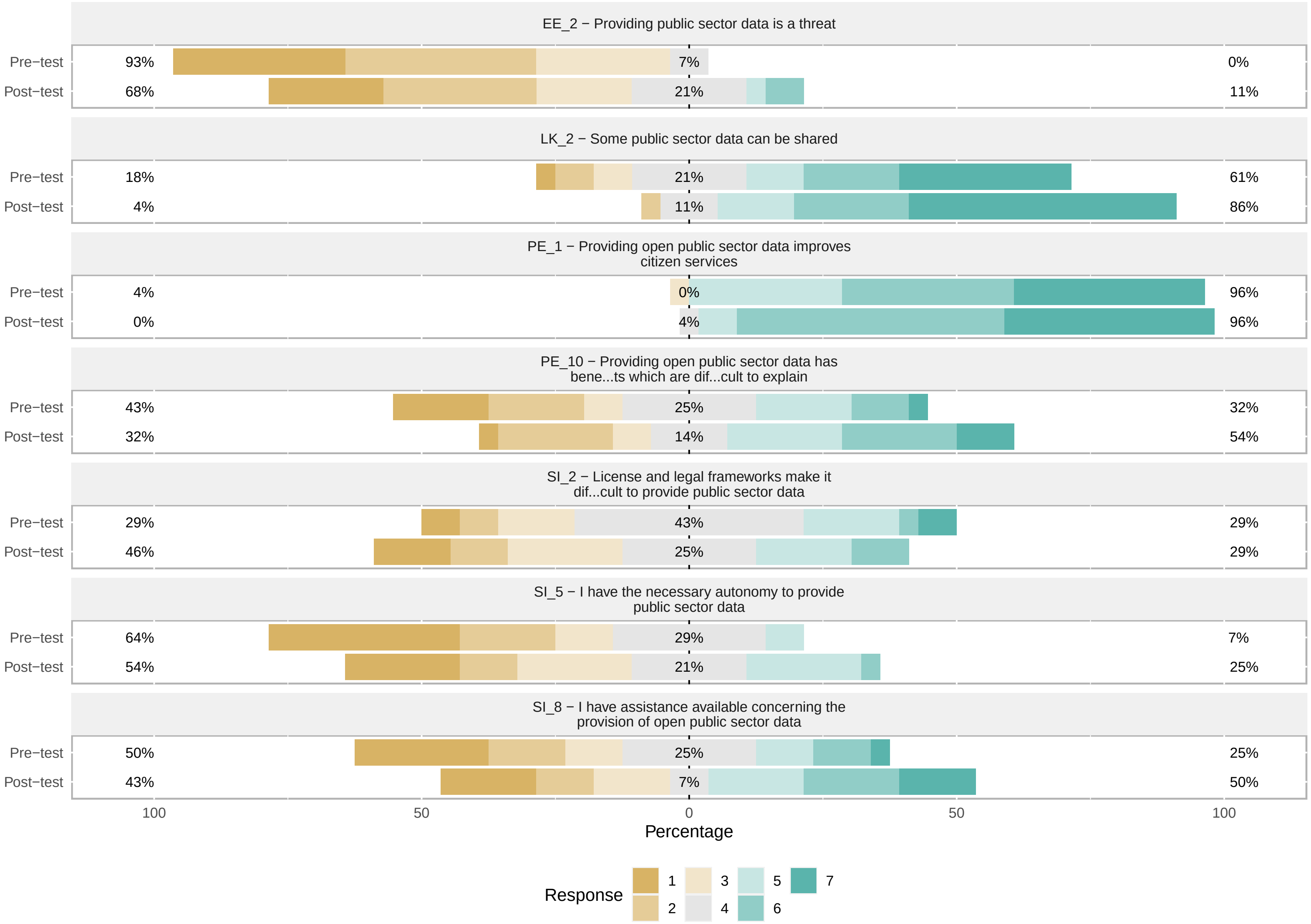

Figure 9 Visualization of the Likert scores for pre-test and post-test items where $p < 0.05$

Table 4 shows the text associated with each Likert item present in both the pre-test and post-test surveys. The table also shows the mean ($\bar{x}$), standard deviation (σ), difference between post-test and pre-test mean ($\Delta\bar{x}$) and p-value (p). The p-value was obtained by performing a paired sample t-test between the two sets of observations. The paired sample t-test or dependent t-test items with $p < 0.05$ were considered statistically significant (Field et al. 2012), with 7 out of 33 items meeting this threshold.

Item LK_2 *(Some public sector data can be shared)* increased from 5.11 to 6.00 with $p = 0.01$. The pre-test score was already high, this is unsurprising given that some of the civil servants were already involved in some way with data disclosure. Still, the score increased by 0.89 between pre-test and post-test - which can be attributed to the effect of in-game group discussions about datasets that players might not have encountered in their work before.

Item PE_10 *(Public sector data has benefits which are difficult to explain)* increased from 3.54 to 4.36 with $p = 0.01$. In this case, the pre-test score started from a low value and increased by 0.82. Seemingly, the game had the effect of making the benefits of open data harder to explain - which is convergent with the effect of the in-game group discussions about the datasets.

Item PE_1 *(Providing open public sector data improves citizen services)* slightly increased from 5.96 to 6.25 with $p = 0.02$. This item - which started from an already high value - saw just a marginal increase of 0.29. The game did not contain any mechanic representing the connection between the opening of public sector data and the improvement of citizen services; the relatively small effect observed on this item is expected.

Item EE_2 *(Providing public sector data is a threat)* went from 2.07 to 2.79 with $p = 0.02$. There was an increase of 0.71 between pre-test and post-test, with the post-test value still remaining low. The changes observed in this item are again convergent with the expected effects of the in-game group discussions, in which players reasoned about the perceived benefits and risks of opening datasets.

Item SI_2 *(License and legal frameworks make it difficult to provide public sector data)* saw a slight decrease from 3.96 to 3.54 with $p = 0.03$. This decrease seemingly shows that participants became slightly less concerned about the obstacles posed by legal frameworks to the opening data. The game did not have any dedicated mechanic simulating legal concerns, so this effect might be attributable to in-game discussions.

Item SI_8 *(I have assistance available concerning the provision of open public sector data)* saw a relatively important increase from 3.29 to 4.07 with $p = 0.03$. The change observed for this item - a positive delta of 0.79 - seems to indicate that participants perceived more support from their colleagues after playing the game. This result can be explained by the group cooperation mechanics present throughout each round.

Item SI_5 *(I have the necessary autonomy to provide public sector data)* went from 2.54 in pre-test to 3.21 in post-test with $p = 0.04$. Even though the post-test score was still low, the increase of 0.68 in this item can be explained by the effect of ownership mechanisms (such as the score summary at the end of each round).

	Description	n	$\bar{x}$	σ
ga_1	I enjoy playing video games	23	5.17	1.80
ga_2	I enjoyed playing Data Belt	23	5.70	1.02
ga_3	The context of my office is well represented by the game	23	3.61	1.67
ga_4	The game changed my perception of data management policies	23	3.96	1.69
ga_5	I know more about the benefits of opening data after playing the game	23	3.57	1.78
ga_6	People in my office know how to make public sector data available for others to access	23	4.13	1.89
ga_7	I know more about the risks of opening data after playing the game	23	4.17	1.80
ga_8	I will open data after playing the game	23	3.83	1.67
ga_9	The game helped me to open more data in my daily work	23	3.30	1.94

Table 5 Results of the satisfaction section of the post-game survey

The satisfaction section (table 5) - included only in the post-test survey - asked participants to self-assess how much they enjoy playing video games and more specifically Data Belt. In addition, this section asks players to give a self-assessment of metrics like knowledge of benefits and risks of open data, that are also assessed using the pre-test post-test analysis. The two items with the highest scores in this section are GA_2 (5.7) and GA_1 (5.17).

The result of GA_1 *(I enjoy playing video games)* had a high score of 5.17, indicating that participants already liked - and probably had experience - playing video games.

Item GA_2 *(I enjoyed playing Data Belt)* had a mean of 5.70, indicating that the game, its mechanics and contents were well accepted by players.

Item GA_3 *(The context of my office is well represented by the game)* saw an average score of 3.61 which seems to indicate that the context of the office was not well recognised by players. This might be because of the digital recreation of the environment - as the in-person version of the game had a different feedback.

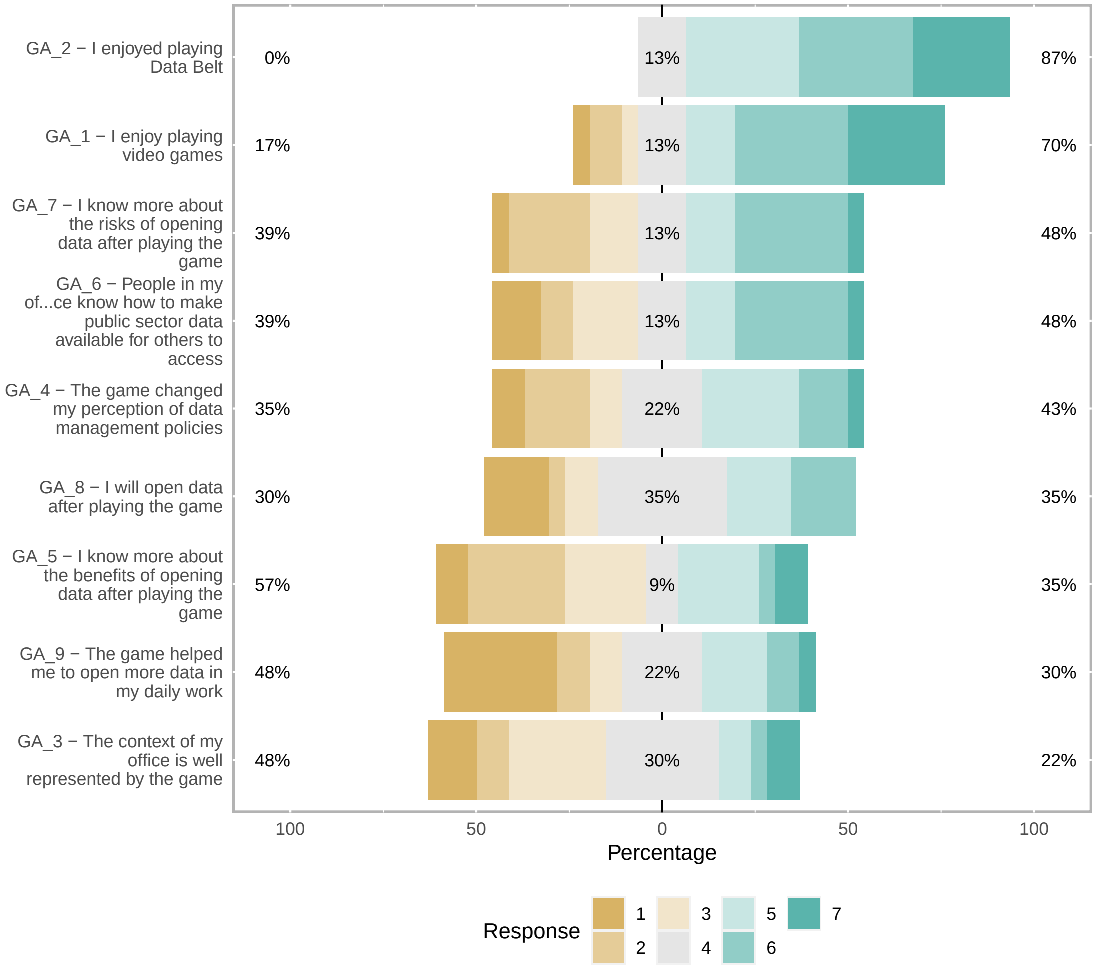

Figure 10 Visualization of the Likert scores for the satisfaction section of the post-test survey

Items GA_4 and GA_5 *(The game changed my perception of data management policies; I know more about the benefits of opening data after playing the game)* had an average of 3.96, which seems to contradict some of the results observed by looking at changes between pre-test and post-test (i.e. item LK_2). This could be explained by the fact that items in the satisfaction section do not rely on a pre-post comparison and are consequently more reliant on players' self-awareness and acceptance of learning outcomes from the game.

Item GA_6 *(People in my office know how to make public sector data available for others to access)* saw a score of 3.83, which, while being low, is close to the score observed in item SI_8 *I have assistance available concerning the provision of open public sector dat)* for the post-test (4.07).

Item GA_7 *(I know more about the risks of opening data after playing the game)* had an average score of 4.17. When compared to effect seen in item EE_3 (from table 4), it seems that the game did not have a generalised effect on all risks related to open data, but rather only on privacy risks.

Items GA_8 and GA_9 *(I will open data after playing the game; The game helped me to open more data in my daily work)* saw respectively average scores of 3.83 and 3.3, which indicate that players do not report that they want to open more data as a result of playing the game. The effect measured by this item is beyond the scope of the game, which was to achieve certain learning objectives with regards to the benefits and risks of open data.

5.4 Summary

This chapter presented the game prototype and compared it to the in-person game on which it is based. Data Belt is real-time multiplayer game for four players, which transposed several components of Winning Data into the online environment, like role-playing, the division in rounds and the phases of data processing and data labelling. Still, several features had to be removed in order to streamline the game and adapt it to the constraints of the remote sessions. The chapter then proceeded to illustrate the results of the one group pre-test post-test quasi-experiment. Data was collected in remote sessions from institutions in Europe and Brazil, with a sample size of 28 participants. The paired samples t-test indicated a statistically significant change in 7 of the 33 Likert items present in the surveys. The pre-test post-test analysis seems to indicate that players agreed more that some public sector data can be shared, but they were also more aware of the associated risks. Furthermore, the perception of support from the colleagues in opening data seemed to shift positively as well. The analysis of the satisfaction section of the post-test questionnaire indicated that the game was well received. However, players did not self-report significant learning outcomes, thus requiring further research to investigate these findings. In the chapter that follows, the answers to the two main research questions will be discussed, along with relevant quotes from the players during the debrief sessions.

6 Discussion

6.1 Introduction

This chapter will discuss the findings presented in Chapter 5 in order to answer the research questions introduced in Chapter 2:

(1) What are the requirements for the design of a digital serious game on the topic of open data?

(2) Which learning outcomes can be observed in civil servants who played the game?

The chapter will start by answering the first research question with the identification of the main game mechanics that contributed to learning and will go on to discuss the results from the quasi-experiment, players' acceptance of the game and their feedback during the debrief sessions in order to answer the second research question.

6.2 Design requirements

The game's purpose was very specific: to provide an environment which roughly resembles a public office in which civil collaborate and discuss whether or not to open datasets. The main mechanics of the game mechanics can be connected to the results the pre-post testing:

Collaboration. The game simulated an environment in which civil servants collaborate very closely and tutor each other on how to follow procedures to process citizens' demands. Since the roles rotate each round, participants need to tutor each other and share knowledge about how to complete the tasks required by each other's roles. Seemingly, this had an impact on the participants' perceived support from their colleagues when opening data, but also on their own autonomy. The game's initial conditions, its rules and role-playing mechanisms were successful at stimulating collaboration. This finding is convergent with the literature on collaborative learning (Dillenbourg 1999), who found that collaboration is a situational event which can be encouraged but not forced.

Questions & Answers. The dataset descriptions presented to the players during data labelling process asked questions about whether or not information contained in a certain dataset prevented it from being opened to the public. This device, which is one of the learning mechanics classified by Arnab et al. (2015), was combined with the incentive to discuss provided by the real-time synchronisation of the players' choices. The result was that most groups actually debated the probable content of a given dataset. Players also provided reasons and insights from their own work or life experience in order to argue for a certain label. It seems that this mechanic led to more players agreeing that some public sector data can be shared, but changing their perception about the perceived benefits and risks of doing so. This finding is convergent with Wendel et al. (2013); Agogué et al. (2015). In particular, the interactions between players resembled what was observed by Wendel et al. (2013): "it is possible to design collaborative tasks in a computer game for training of collaboration. We could observe the players to talk to each other about problems to be solved in the game, thus discussing their working relationships, helping and promoting each other's success".

6.3 Learning outcomes

The comparison of pre-test and post-test surveys highlighted that players were more likely to accept that some public sector data can be shared after playing the game. Similarly, participants were more likely to recognise that open data has some benefits and threats and that they have the necessary assistance and autonomy to provide it. Finally, participants had a good acceptance of the game - even though they did not think it offered a good representation of their office.

The game prototype was successful in creating an enjoyable experience for the majority of players in the sample. Some players observed that the game did accurately reflect the environment of their office and the difficulties of conducting bureaucratic procedures associate with service delivery in the public sector. However, the game was not very effective at showing the consequences of incorrect decisions about data disclosure, as stated by one participant during the debrief session:

> I don't see the consequences for clicking the wrong box, apart from the boss not being able to do the press conference...that's it. I mean, I want to see chaos ensuing, I want to see all the criminals now started to target the same house every night, there is chaos on the streets and the mayor resigned.

Other players complained about the lack of clarity of the datasets' description:

> I found it a very confusing game. The intention, the goal wasn't clear to me. In the end it appears that under hard pressure you have to decide whether some data should be open, shared or private. It took a lot of time a lot of time to figure out exactly what the data was that should be open, shared or private.

This observation is consistent with comments made during other debrief sessions. Notably, the datasets' description was made intentionally vague in order to stimulate discussion. In fact, part of the game's objective is to figure out the content of the datasets starting from a basic description. Given the rules and incentives of the game, making a dataset description too specific would have meant an obvious decision and lack of discussion.

For some groups, the debrief session sparked a discussion on the misconceptions and obstacles related to OGD. One player, who has worked for an office in charge of deciding whether or not to open certain datasets, touched upon some of the barriers to the opening of data highlighted during the literature review in Chapter 3:

> When data is requested from a supranational institution like the [EU] Commission the property of the data is shared by the Commission and the Member States. Some Member States are lax and have no problem opening all datasets, others are more circumspect. [...] You could safely release the data on how many farmers raise cattle of a certain breed in Italy, because there is many of them and identification (singling out any individual) is very difficult. In Sweden it isn't the same, there are very few of them and it is extremely easy to understand who is performing the activity within a certain region or province. So, for example, Sweden, which usually releases a lot of data, is quite restrictive on this datasets.

As shown by this quote from the debrief session, part of the learning process continued during the debrief session itself, with participants sharing anecdotes and experiences about open data. This is convergent with the literature discussed in section 4.4 ("Debriefing").

Insight into the game's acceptance by the players is given by the self-reported learning goals and satisfaction with the game (table 5). Results indicated that most players already enjoyed playing video games. This is unsurprising, given that some of the participants were recruited through mailing lists and thus it is expected that employees who already like video games might be interested to join the experiment. Further research should investigate whether the game is still effective in participants who have little experience playing video games. The survey results also highlighted that the game was well liked by players, thus making it reasonable to conclude that players accepted the idea of a game about open data and had fun playing it. Still, it seems that the context of the office was not well recognised. As mentioned in the section about collaborative learning (3.4), one of the great challenges of translating a game into an online setting is the lack of tactile feedback and hand or body movement. In fact, Winning Data (Kleiman et al. 2019) relied heavily on player movement and physical objects; players would need to walk from a table to another, throw dice, transcribe information and collect cards, among other things. Winning Data did receive positive feedback on its resemblance to the players' workplace and so it might seem that in the translating the game to a digital format something was lost. Interestingly, players did not self-report having changed their perception of data management policies or knowing more about the benefits and risks of open data, even though this is conflict with the findings from the pre-test post-test analysis. It is possible that players might not be willing to self-report learning outcomes coming from the game, or they might not be aware of them right after finishing the game session, but further research is needed to investigate these effects.

6.4 Summary

In this Chapter, the two research questions of this research were answered. For the first research question ("What are the requirements for the design of a digital serious game on the topic of open data?"), the two main design requirements - collaboration and questions & answers - were synthesised. While collaborating, players helped each other, leading to an increased feeling of support from their colleagues. The second main element, questions & answers pushed the group towards analysing the risks and benefits of opening a certain dataset. During the discussions, players shared with each other knowledge and past experiences with open data decision-making, which is crucial to achieve learning. Finally, the learning outcomes of the game were discussed using quotes from the players during the game session debrief. After playing the game, participants tended to agree more that some public sector data can be shared, and were also more aware of the risks and benefits. The game was overall well received, but the debrief sessions highlighted that consequences for incorrectly labelling datasets were unclear and some players found the datasets' descriptions vague.

7 Conclusion

7.1 Main conclusions

This thesis began with two main objectives: to find the design requirements for a digital game about open data and to observe its learning outcomes. In Chapter 3, the concept of OGD was introduced and its applications, benefits, threats, risks and barriers from the existing literature were presented. OGD was found to be a powerful tool for citizens and journalists, enabling government accountability and the creation of innovative applications that can fill some of the gaps in public services. At the same time, OGD presents threats to individual and group privacy and can be especially dangerous for vulnerable minorities, when these threats are not taken into account. The literature review also found that civil servants tasked with making decisions about the release of OGD are often understaffed and need to make decisions quickly and in an uncertain environment. The decision-making process is also influenced by the risk of exposing governmental organisations to unwanted scrutiny and real or perceived barriers regarding laws and regulations and the hierarchical structure of the administration. Given this environment, there is a need for a tool to train civil servants engaged in open data decision-making. The literature review proceeded to define the concept of serious games and found several examples in the context of open data. Winning Data (Kleiman et al. 2019) is one such example which was tested on civil servants and which managed to achieve learning objectives connected to OGD. Winning Data, which requires in-person participation, was used as a basis to build Data Belt, the new digital collaborative game for this thesis. In Chapter 4 the methodology used to develop the game prototype was presented. The main features to be maintained from Winning Data were picked. Next, the desired game mechanics and learning mechanics were chosen and mapped following the LM-GM framework by Arnab et al. (2015). The methodology used to assess the learning outcomes was also presented and was largely similar to Kleiman et al. (2019). Finally, Chapters 5 and 6, presented the results of the one group pre-test post-test quasi-experiment and of the satisfaction section in the post-test survey which inquired about acceptance of the game and self-reported learning achievements. In the discussion, relevant quotes from the players during the debrief session were also used. The results seem to indicate that the game was effective at facilitating learning about the benefits and risks of open data. Furthermore, participants were more likely to open data after playing the game. Still, there are significant limitations (as explained in more detail in the next section) and the results observed in the pre-test post-test analysis are somewhat contradicted by the self-reported items in the post-test survey.

This research contributes to the existing literature by showing that serious games can potentially be used to train civil servants involved in open data decision-making, even in a virtual setting. The implications for practitioners is that serious games do have a space as a learning tool and when designed appropriately can leverage the benefits of collaborative learning. Data Belt was able to engage players in discussions about open data, during which they shared their experiences and knowledge about the topic with each other.

7.2 Limitations

This study main limitations include the small sample size ($N = 28$) and lack of control group, which make it harder to establish the relationship between the game and learning outcomes. In further research, the presence of a control group subject to another form of training (like reading materials or a presentation) can offer an important benchmark to establish the effectiveness of the game. Additionally, the sample was not randomised and, as shown in chapter 5, included mostly people who already liked playing video games. In some cases, some employees were directly invited by a secretary or other administrative staff in order to fill game sessions, again without randomisation. Given the remote setting of the game, it was not possible to control for some environmental variables like exact time and day at which the pre-test survey was filled and the kind of device used to play the game. Pre-test surveys were sent a couple of weeks before the game sessions and participants were free to fill them at any point before the beginning of the session. It is also reasonable to assume that because the game was played at home by civil servants during their working hours, some distraction from the experiment happened in the form of email notifications or other work-related tasks. In order to accurately match pre-test and post-test surveys, participants were asked to input their email address into the questionnaire. An accompanying message explained that the email would only be used to match pre and post-test answers and that it would never be used to identify a player. Still, by requesting the email address, the sense of anonymity of the questionnaire might have been partly compromised. For these reasons, the environment in which the surveys and game sessions were conducted is a quasi-experimental one, as there are a number variables outside of our control.

Regarding the debrief, players were asked collectively to give some feedback or first impressions about their experience. Clearly, participants might be influenced by the observations made by the first person to speak and their feedback could be skewed accordingly. A further bias might have been caused by the facilitator identifying himself as the developer of the game at the beginning of the session.

7.3 Future work

Future research could offer a direct comparison between the in-person game Winning Data and the digital game Data Belt, in order to better clarify which are the most difficult aspects to translate into an online environment. Future experiments should also have a control group (which, for example, is presented traditional educational materials such as leaflets) in order to remove the influence of external variables.

In the current game players spent a significant amount of time guessing the exact content of each dataset before making a decision on whether or not to open it. In a future game, decisions should concern more the politics, ethics and risk-taking associated with decisions on data disclosure. One possible solution is to remove the *reference label* and do without right answers. This solution would remove the need for players to guess the literature's recommended actions on certain datasets, which might be differ with local or national policies on OGD. Instead, players would simply be asked to make their own judgement and see the consequences or their decisions, each with certain benefits and drawbacks. For example, a decision to disclose more data regarding a rare disease might lead new scientific findings, but, because the dataset was very small, some patients might now be identifiable.

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