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Understanding digital platform evolution using compartmental models

Gabriel Andy Szalkowski [a,*], Patrick Mikalef [b,c,d]

[a] Department of Information Security and Communication Technology, Norwegian University of Science and Technology, A-bygg A111, Teknologivegen 22, 2815 Gjøvik, Norway
[b] Department of Computer Science, Norwegian University of Science and Technology, Sem Sælandsvei 9, 7034, Trondheim, Norway
[c] Department of Technology Management, SINTEF Digital, S.P. Andersens Veg 3, 7031, Trondheim, Norway
[d] School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia

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ABSTRACT

Due to the growing impact of digital platforms, it is increasingly important to understand their evolution through mathematical models. As their value is dependent on their user base, we present an improved perspective on modeling the number of users. Modeling digital platforms is frequently constrained by the scarcity of available data. Thus, researchers resort to open access data like Google Trends. We provide a new interpretation of such data, using it as a proxy for the demand, in contrast with the previous method of considering it as the active user-base. This is implemented using compartmental methods, in which the expression of the demand is fitted to the number of Google Searches for a specific keyword. Two cases, the MMO World of Warcraft and Facebook are analyzed in this fashion, using two different compartmental models. The solutions given by both models replicate key features of the real evolution of the services at study, and the parameters of the fit are in accordance with the expected relative values.

1. Introduction

Digital platforms have become one of the most important sources of economic activity over the last decade, radically changing how we work, socialize, create value in the economy, and compete for the resulting profits. Digital platforms have been defined as multi-sided digital frameworks that shape the terms on which participants interact with one another. A key tenet in digital platform research is that such platforms become more useful and of value, the higher the concentration and interaction of users, a notion termed network effects. Nevertheless, one of the key challenges in understanding the evolution of digital platforms is identifying emerging trends of user interaction and usage.

The owner of a small online business finds that the service they offer stops working for technical reasons due to a sudden increase in popularity; too many users have collapsed the service. A social networking business that was doing well starts losing its customers, and it is too late to stop them in time before the consequences are too dire. What these two scenarios[1] have in common is a lack of information about future changes in the user base of a digital platform. Such cases constitute the motivation behind the research question of this paper: How can we more accurately and transparently capture the dynamics behind the trends in evolution of a digital platform?

This is a relevant question, as thanks to the proven advantages of the use of digital platforms (Chatterjee et al., 2022), more and more businesses are embracing a digital transformation (Bughin et al., 2017), basing their activity on platform business models. Due to this fact, it is becoming increasingly important to study the evolution of digital platforms (McIntyre and Srinivasan, 2017; Rong et al., 2018). In this era, the era of Big Data and rapid evolution of technologies, we are in need of new approaches and tools to tackle the problem of describing the long-

* Corresponding author at: A-bygg A111, Teknologivegen 22, 2815 Gjøvik, Norway.
E-mail addresses: gabriel.szalkowski@ntnu.no (G.A. Szalkowski), patrick.mikalef@ntnu.no (P. Mikalef).

[1] Although these are hypothetical cases, one could refer to real website crashes do to unexpected high traffic that can affect even the biggest services, like Spotify or Amazon (Morand, 2023). Some real examples related to the second scenario would be social networks like Friendster or Google+ (Hollingsworth, 2022).

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term evolution of digital platforms, methods that offer transparent and analytical explanations of the underlying dynamics of their evolution (Rong et al., 2018). Thus, although the reasons behind that evolution are very important (McIntyre and Srinivasan, 2017), we focus our study on a macro-level depiction of the markets, a perspective with a history of usage for general market forecasting and competition modeling (Wang & Wang, 2016a). The increased understanding provided by these models could help us to take action towards improving the long-term performance of digital platforms.[2]

This research makes a contribution in the field of digital platform modeling and forecasting. We aim to find a deterministic explanation of the behaviour and the evolution of digital platforms (like social networks or online video games), whose value is completely dependent on the number of users they have. Although it is still a relatively young field, the literature presents several distinct approaches, adapted from other areas of economics and mathematics. A common approach is using the Bass diffusion model (Bass, 1969), modifying it and adapting it to a specific market, like smartphones (Singhal et al., 2020), pharmaceuticals (Guseo and Guidolin, 2011), or Fiber-to-the-home services (Velickovic et al., 2016). Another common approach to mathematical market modeling is using Lotka-Volterra predator-prey equations, adapted for describing competition between services like mobile network operators (Marasco et al., 2016a) or operating systems (Marasco et al., 2016a). Both approaches are often compared, like done in (Chang et al., 2014). The mathematical methodology chosen for this research are Compartmental Methods, a technique adapted from epidemiology, based on segregating a population into different compartments or groups and modeling the transitions between those compartments. We model those transitions using the Bass model. For more details on this procedure, refer to Section 2.2.

Even though these mathematical models can be of great utility by themselves, in order to be applicable to real markets they need external data as an input. Given the frequent problem of data scarcity (Bansal et al., 2022), this can be a difficult task, both for researchers in the field of digital economics and for business owners that look for reliable information about the current state of their company and its future prospects. Due to the popularity of Google Search engine, we argue that the tool Google Trends is a potential source for the much needed data. Google Trends[3] is a popular, publicly available tool that provides the historical search query data for a specific term, presenting the normalized volume of Google searches during a period of time. The fact that this data is publicly available makes this tool easy to use and accessible. This kind of data is of great value (Wang & Wang, 2016a), as it can be used as an approximation for the real data of interest or usage of a service (see Section 3). The idea of using this tool was further motivated by the increasing interest in using Google Trends as a tool for forecasting. This trend of usage represents a shift of focus towards Google Trends data, initially used mainly for surveillance and monitoring (Jun et al., 2018).

Compartmental methods and Google Trends had already been combined for the purpose of modeling the evolution of digital platforms (Cannarella and Spechler, 2014). However, the approach to these data followed in (Cannarella and Spechler, 2014) had proven to be ineffective, yielding inaccurate results. This was evidenced by their conclusion that Facebook would lose 80 % of its user base between 2015 and 2017, a result that differs greatly from what happened in reality (Dixon, 2022). Therefore, we argue in favour of a change of perspective for using (publicly available) Google Trends data to describe and forecast the evolution of technologies, services and platforms, based on considering the data as a proxy for the demand[4] rather than the total number of users. We provide examples of how to apply this new consideration in practice with the help of compartmental methods (using an established model for these purposes and a novel model designed specifically for this study), and we present some examples of application, studying Facebook and World of Warcraft.

In summary, this paper aims to add to the existing body of knowledge on digital platform modeling by exploring a new interpretation of the historical trends data provided by Google Trends, taking it as in input for the demand in compartmental models of digital platforms. In addition, we aim to develop a systematic modeling scheme for understanding digital platform dynamics, based on comprehensive mathematical tools, in contrast to the increasing trend of using artificial intelligence and machine learning (often described as "Black Boxes" (Quinn et al., 2022)) for those purposes. From a practical perspective, this research contributes by providing an open access tool with a transparent methodology for interpreting early signs that may uncover substantial future changes in the user base of a digital platform. This can aid taking informed action when an increase or decrease in the user base is expected.

2. Theoretical background and prior research

In order to provide more insight into the basic tools used in this research we present a short description, with the help of a brief overview of the existing literature related to them.

2.1. Usage of historical trends

In general, Historical Trends data is data that records instances of a phenomenon happening over time. These records can be used as a tool for understanding a phenomenon, making predictions about future outcomes, or taking more informed decisions. In fact, the usefulness of this kind of data had been well understood since the early stages of Human History. Early use of Historical Trends dates back to the Lebombo bone (35,000 BCE) (Apostolou and Crumbley, 2008), an artifact found in Swaziland that was used for keeping track of the lunar phases. With the advent of the internet, using tools like Google Trends, it is easier then ever to gather this kind of data, as we shall present throughout this section.

Google Trends is our tool of choice for gathering data about demand due to accessibility and ease of use. As an open access tool, it provides several great opportunities for research, but it also comes with its shortcomings. First, the normalization of the data is automatic, so the exact number of queries is never known. We present an interpretation to help dealing with this issue in Section 3.2.1. Despite this limitation, Google trends has been a services widely used in research. The following examples show how it had been exploited (with limitations) to gather data in areas like healthcare and economics, as well as a tool for estimating demand.

One famous application of Google Trends had been Google Flu Trends (Dukic et al., 2012; Tobias Preis and Helen Susannah Moat, 2014), where data on Google searches for flu-related terms were used for estimating and predicting the reach of flu outbreaks. Although some research as (Dukic et al., 2012) looked promising, the Google Flu Trends

[2] The term digital platform refers here to any online infrastructure that enables interaction between users. For a discussion on the definition and characteristics of such platforms, we refer to (Bonina et al., 2021). Throughout the text, we sometimes refer to digital products and services which, in the context of this paper, comprise mainly software products and online applications. In some cases, "digital platforms" and "digital products/services" can be used as synonymous terms: Facebook is a digital platform, and the service offered by Facebook is a digital service, so we could refer to Facebook itself, by extension, as a digital service. The markets of these digital products and services are digital markets (Øverby and Audestad, 2021a).

[3] https://trends.google.com/.

[4] The demand in this study is understood as the number of new incoming users at a given time. Mathematically, it can be regarded as the positive part of the derivative of the number of users. In this context, the concrete definition of the demand depends on the model used. We address this topic more in depth in *Sec.* 3.

project resulted in failure, as explained in (Lazer et al., 2014), exemplifying the limitations of the tool. Despite those limitations, and given its history of epidemiological applications, Google Trends data has also been used to study the Covid-19 pandemic (Hu et al., 2020; Fantazzini, 2020; Nikolopoulos et al., 2021). For a review and analysis of Google Trends as a tool in healthcare research, refer to (Nuti et al., 2014; Arora et al., 2019).

Google trends has gained interest in the field of economics and social studies, being used for predicting, for example, automobile sales and unemployment claims (Choi and Varian, 2012) or for forecasting the performance of exchange rate models (Bulut, 2018). Moreover, in the field of digital economics it has become a useful tool. One case is the modeling of the price of Bitcoin (Kristoufek, 2013). For this research, however, we are more interested in user-base and demand modeling, like (Garcia et al., 2013), where the evolution and decline of social networks is studied. Another example of this scenario is (Cannarella and Spechler, 2014), where the Google Trends data of searches for the keyword *Facebook* is used as an input for an epidemiological model to study the evolution of social networks. Although the predictions given in (Cannarella and Spechler, 2014) for Facebook had proven to be wrong, the methodology is a starting point that in part inspired this paper.

One of the reasons that the results of (Cannarella and Spechler, 2014) may have proven wrong could be that the number of queries is treated as the total number of users, rather than a quantity like the demand or the number of incoming users. Although this perspective is quite new in this context, there are multiple examples of using Google Trends as a proxy for the demand, like (Doepker et al., 2022) where this data is used to predict the state demand of radiologists, or (Huarng et al., 2020; Luze et al., 2020), where, respectively, the demand for housing and plastic surgery is studied. One of the fields that has gained attention is predicting the inbound tourist (tourism demand), using Google Search query data (Önder, 2017; Bokelmann and Lessmann, 2019; Feng et al., 2019) as an estimation of the number of people that will visit a region. However, we have been unable to find any publication that follow this approach in the digital economy, in the sense of using Google Trends data as the number of users that register in a service, buy a game or create an account. The rationale behind our decision of making of this our main hypothesis is explained in Section 3.1.

2.2. Compartmental methods

Compartmental methods are a relatively simple and explainable procedure to describe and forecast the behaviour of a population, in contrast to for example machine learning techniques. The first steps are always defining the compartments in which a population would be divided and how individuals transition from one compartment to another. The dynamics of the evolution of the populations of each of the compartments can be written in terms of differential equations. For a better understanding of the technique, we shall examine the most famous example, the SIR (Susceptible, Infectious, Recovered) model, where the healthy population in the Susceptible compartment can transition to the Infected compartment by contact with an infected individual, who in turn move to the Recovered category spontaneously with time. This model dates back to the mathematical epidemiology papers (Ross, 1916; Ross and Hudson, 1917), written in 1916 and 1917 respectively.

Let us present a brief explanation of the simplest SIR model (see Fig. 1), to help with the understanding of the technique. Inside a mostly healthy homogeneous and large population (Susceptible) there are some people infected with a transmittable disease (Infectious). After some time, the infected people recover and stop spreading the disease. The rate at which people get infected will be thus proportional to the total number of susceptible individual and the number of infected people, and the rate of recovery would only be proportional to the number of infected individuals (the more people get infected, the more people recover). This can be translated in a set of linear differential Eq. (1),

$$\begin{aligned} \frac{dS}{dt} &= -\alpha SI \\ \frac{dI}{dt} &= \alpha SI - \beta I, \\ \frac{dR}{dt} &= \beta I \end{aligned} \tag{1}$$

using a "−" sign for outgoing flows and a "+" sign for incoming flows.

Compartmental models have been adapted and used for not only epidemics, like modeling the COVID-19 pandemic (Ramezani et al., 2021), but also in several other contexts, such as the spread of ideas (Bettencourt et al., 2006), rumors (Afassinou, 2014; Wang et al., 2014) or misinformation on social media (Maleki et al., 2021). In relation to this research, we must point out that this type of modeling has gained interest in the realm of digital economics. One example is the aforementioned work on the evolution of social media user-bases (Cannarella and Spechler, 2014).

More complex models have been developed based on the Bass model (Bass, 1969). In this type of compartmental models, the basic idea is that the flow between the compartments follows the Bass diffusion model. For example, potential customers become customers spontaneously or by influence of other users. A comprehensive overview of this procedure can be found in Chapter 18 of (Øverby and Audestad, 2021a). Some use cases in the digital economy of compartmental methods are the classification of multisided platforms (Øverby and Audestad, 2021b), the study of the dynamics of the users of video games (Øverby, 2021; Øverby and Audestad, 2019), competition and churning between streaming services (Idland et al., 2015) and mobile telephony companies (Centrone et al., 2007).

As mentioned in Section 1, procedures that use the Bass model have been compared to Lotka-Volterra competition models. Although phenomena like network effects and churning are possible to model using the latter option (Marasco et al., 2016a), we believe that compartmental modeling is conceptually and methodically easier for achieving the purpose of this study. It is easy to see that both approaches can describe scenarios that exhibit logistic growth and interaction between services: (Marasco et al., 2016a) using Lotka-Volterra equations, and (Øverby and Audestad, 2021a) (Chapters 11 and 18) using Compartmental Modeling.

3. Methods

In this section, the procedure of our approach to analyzing the data from Google Trends is outlined, starting by our interpretation of its meaning and describing afterwards how to implement it using compartmental models.

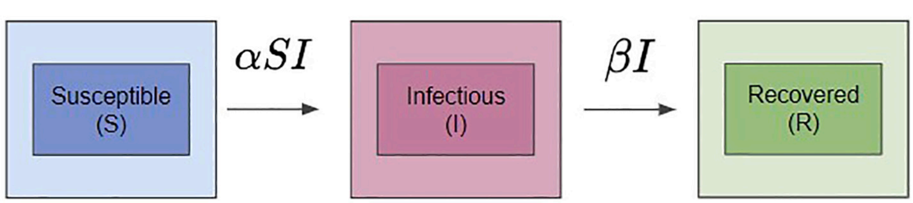

Fig. 1. Compartmental depiction of the SIR model.

3.1. Demand as proportional to Google Trends

The main hypothesis of this work is that data from Google Trends of the number of search queries about a certain service can be used as an indicator of the demand for digital products and services, like social networks or video games. This is different from the existing approach of using it as an indicator of the total number of users, like done in (Cannarella and Spechler, 2014). The logic behind this perspective is clear if we consider the following example. Assume that we want to study the evolution of the user-base of an online video game. The typical process of acquiring the game could be first searching for the game through an internet browser, buying it, downloading and installing it, and start playing. There has been just one instance of searching for the game; the player will neither look for the game nor install it every time they want to play it. A similar case would be the number of users of Social Media services like Facebook, a case where after creating an account the most common way of accessing the service is though the mobile application or bookmarks on a mobile device (just 1.5 % of users access Facebook though desktop only (Dean, 2022)). Therefore, we assume that the number of Google searches would be more similar to the number of new accounts rather than the total number of users.

3.2. Compartmental model analysis

In order to implement these considerations we must first define what we mean by demand in this context. In compartmental market models, we can define different types of users, segments of the population, etc. However, one distinction will always be present: we can always classify the individuals in the system into users and non-users. The flow from the compartments labeled as non-users to the compartments labeled as users is what we define as demand. In other words, the demand is the number of individuals that in a given time period start using a product or service. The exact mathematical expression of the demand will depend on the model we are working on.

3.2.1. Normalization

One of the downfalls of the data obtained from Google Trends is that it is normalized so that the point with the maximum number of searches is 100. However, due to the stochastic nature of the number of daily queries there is a noticeable level of variation from day to day, which means that the peak that represents the maximum number of searches is likely not a good reference point. Therefore, we chose to re-normalize the data so that the area under the data is one. In other words, if the demand (incoming customers per unit of time) is proportional to the number of Google searches, the integral of the demand (total customers that the service has had) represented by those searches is 1, or 100 %. This is the same as studying the fraction of the total customers at a given time, rather than the total number of customers, which is unavoidably unknown.

3.2.2. Fit to data

The general procedure for fitting the models to the Google Trends data is the following. Once a model for describing the evolution of the market is defined (a set of compartments with populations $\{A(t), B(t), C(t) \ldots\}$ and the flows between them, mediated by the flow parameters $\{\alpha, \beta, \ldots\}$), the expression for the demand is calculated adding up all the incoming-users flows. This expression is a function of several parameters (depending on the model) that will be fitted to the query data. By design, in our models these flow parameters are considered non-negative constants.[5]

The basic idea behind the fit is minimizing the output of a function. We need to define a function that takes the flow parameters as an input and returns a numeric value that we will minimize. This value is the absolute value of the difference between the demand given by the model and the normalized number of Google searches.

First, we need a function that takes a defined set of flow parameters $\{\alpha, \beta, \ldots\}$ and returns the solutions to the set of differential equations that describe the model. These solutions are the populations of the compartments over time $\{A(t), B(t), C(t) \ldots\}$ in the time interval at study. To obtain them, we always use the same set of initial conditions $\{A(0), B(0), C(0) \ldots\}$ for each model. With the solutions $\{A(t), B(t), C(t) \ldots\}$, we calculate the expression for the demand specific to the model. We then normalize the result obtaining the function $D(\alpha, \beta, \ldots; t)$, the normalized demand of the model as a function of time for a given time interval and a set of fixed flow parameters.

$\{\alpha, \beta, \ldots\}$.

With the normalized demand function $D(\alpha, \beta, \ldots; t)$ and the appropriately normalized number of Google searches $G(t)$ for the same time interval, we define the function to minimize,

$$m(\alpha, \beta, \ldots) = \sum_{t=0}^{t_{final}} |D(\alpha, \beta, \ldots; t) - G(t)|, \tag{2}$$

which is the sum of the absolute differences between the demand of the model and the Google Trends data. The calculation of the function $m(\alpha, \beta, \ldots)$ can be summarised as:

1. For a fixed set of initial conditions $\{A(0), B(0), C(0) \ldots\}$ and flow parameters $\{\alpha, \beta, \ldots\}$, solve the differential equations that describe the model to get $\{A(t), B(t), C(t) \ldots\}$.
2. With $\{A(t), B(t), C(t) \ldots\}$, calculate the demand for the model $D(\alpha, \beta, \ldots; t)$.
3. Find the absolute difference between the demand of the model and the number of Google searches using eq. (2).

The final step to perform the fit is to find the set of flow parameters $\{\alpha_0, \beta_0, \ldots\}$ that minimize the value of $m(\alpha, \beta, \ldots)$. We chose to perform the procedure using the programming language Python. For the optimization, the SciPy[6] library was used. The minimization of $m(\alpha, \beta, \ldots)$ was achieved using the Broyden–Fletcher–Goldfarb–Shanno algorythm (explained in (Fletcher, 2013)).

4. Results

In order to portray the results of this study, we applied two different models, the BPQ (Buyer-Player-Quitter) model as described in (Øverby and Audestad, 2021a) and one new model (which we call PHLoQui, Potential-Hesitant-Loyal-Quitter), for describing the evolution of the Massively Multiplayer Online Game (MMO) World of Warcraft and Facebook. We have chosen these models because the first one is an established model that has been applied for modeling user-bases of digital services before (Øverby, 2021; Øverby and Audestad, 2019; Øverby et al., 2023), and the second one has been specifically tailored for the purpose of this paper. The purpose of introducing the PHLoQui model is describing more complex phenomena without adding too much complexity. We show in these practical scenarios how to implement our hypothesis of treating the number of Google Search results as a value proportional to the demand, comparing the performance of both models.

4.1. BPQ model

4.1.1. The model

The Buyer-Player-Quitter (BPQ) model is a compartmental model used for describing the evolution of a subscription service, such as a video game (Øverby, 2021). A more detailed explanation can be found

[5] More advanced models could treat the parameters as time-depending functions. This is left for future studies.

[6] https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.minimize.html.

in (Øverby and Audestad, 2021a). It is based on three compartments (see Fig. 2): Buyers, potential customers that could join the service; Players, active users of the service; and Quitters, people that stopped using it. The flow between the compartments follows the Bass model, with Imitators and Innovators. For example, people may buy a game because others did so (imitators) or because of other reasons independent of the number of players (innovators).

4.1.2. World of Warcraft

The choice of the MMO World of Warcraft had been made to build upon the study in (Øverby, 2021). Using the procedure outlined in Section 3.2, having defined the demand as the incoming players, $D(a,b,r,s;t) = (a + bP)B + (r + sP)Q$, we perform a fit to the number of Google Searches for the keyword 'wow', a commonplace abbreviation of the name of the game. The resulting curves for the population of the compartments are presented in Fig. 3.

From the results of the fit, we can draw some interesting conclusions about our model. We know that the peak of Google Searches happened around 2008–2009, but the maximum number of players of the game was reached in late 2010 - early 2011 (Gilbert, 2015). This delay is captured in the results, where the maximum number of players is reached around the same time as in the real case. It is important to note that the only input here has been the number of Google Search queries for the word 'wow', with no information about the time evolution of the number of players. The results also show that the user-base has been declining after reaching the maximum, a behaviour that is also compatible with the real case and the data presented in (Øverby, 2021). The time offset between the point of maximum demand (maximum Google Search queries) and maximum user-base is shown more clearly in Fig. 4.

4.1.3. Facebook

Our second study scenario is the social medium Facebook, a case where the user-base does not decline, even though the apparent demand does. In fact, although the growth is slowing down (Dean, 2022), the user-base is still growing (Dixon, 2022). We use this example to show that our procedure is capable of replicating both behaviours, a service that declines with time (World of Warcraft) and a service that apparently[7] reaches saturation, such as Facebook. The resulting evolution of the compartments of the BPQ model after of fitting the demand to the number of Google Searches for the keyword 'facebook' is presented in Fig. 5.

Comparing the resulting evolution to the real data, we find that the behaviour is very similar for the period depicted in (Dixon, 2022). The most important characteristic is the apparent saturation of the user-base, captured by the model too. One result of the model is that very few people quit using Facebook. This could make sense in the context that people do not delete their accounts and most of the users continue using the service, even if they do so to a lower extent. However, we have not been able to gather data to confirm this hypothesis. If we zoom-in to the population of the *Quitters* compartment, we can see that the number is not exactly zero, but it starts to grow with time (see Fig. 6). This might be a hint (although it is hard to conclude anything at this point) that the user-base of Facebook could start declining some time in the future.

From the values resulting from the fit (see Fig. 5), we see that in every flow the most important contribution is due to the imitators. This could be a consequence of strong network effects present for this platform.

[7] Although we cannot conclude anything with a 100 % certainty about the future of Facebook, the model shows an apparent trend in user behaviour, similar to common trends in other digital markets (Øverby and Audestad, 2021a).

4.2. PHLoQui model

4.2.1. The model

The Potential-Hesitant-Loyal-Quitter (PHLoQui) model is a compartmental model designed as a part of this study. It consists of four compartments, based on a clear distinction between users and non-users (see Fig. 7). The users or customers are divided into Hesitant (people that will, at some point, stop using the service) and Loyal (people that adopt the service and never stop using it). The non-users can be potential customers (people that will at some point adopt, temporarily or permanently, the service) and Quitters (people who have tried the service, but stopped and will never try it again). We start from the basic assumption that the only observable quantities in some way are the number of customers and the total population of (real and potential) customers. Thus, we can only know the value of the sum of the Loyal and Hesitant compartments, and the sum of the Potential and Quitters compartments. Therefore, the network effects (imitation terms) in the Bass model will be proportional to the value of these sums.

As we can see in Fig. 7, there are five flows between the compartments. The flows whose sum constitutes the demand (customers joining the service) are shown in blue color: $D(a,b,c,d;t) = [a + b(H + L)]P + [c + d(H + L)]P$. Please note how the effect of the size of the user-base on the decision of new users to join the service is quantified as the sum of the Loyal and Hesitant customers (total user-base). Although some of the parameters are not explicitly present in the definition of the demand, the evolution of the different compartments' populations gives rise to implicit interdependencies, which result in the demand being modified by the value of those parameters.

We see two outgoing green flows from the Hesitant Customers compartment in Fig. 7, one to the Quitters compartment and one again to the Potential Customers compartment. These are designed in such a way that people can quit because of external or personal reasons or because other people have quit. However, users do not know if the people that left the service will re-join or not. Finally, as it is not possible to know how many Loyal customers there are, Hesitant customers are only able to become Loyal customers for external or personal reasons, such as loyalty programs or big appreciation of the service.

One example (from another context) to understand the model better could be the case of smokers. One person that never smokes (potential customer) starts smoking. They could have done it because of other people (Hesitant and Loyal smokers) doing it being then an imitator, or for other reasons, like simple curiosity, becoming an innovator. If the person never quits smoking, they are considered a Loyal customer. However, a person may quit and relapse several times, going back and forth between Potential and Hesitant customer, or quit forever (Quitter).

4.2.2. World of Warcraft

Acting in the same way as with the BPQ model, we fit the demand and obtain the curves for the evolution of the different compartments. The time evolution of the customers' compartments is re-scaled and depicted together with the demand in Fig. 8. The evolution of the non-user compartments has been omitted in the figure for clarity. We can see in Fig. 8 that there is a small delay between the maximum of the demand and the point of maximum user-base. This delay, although captured by the model, is considerably smaller than the real one. In that sense, the BPQ model offers a better description. However, both models are able to capture the general behaviour of the number of users, presenting an initial peak followed by a decline and a state with a relatively stable low user-base.

The results of the fit suggest that the adoption of World of Warcraft by the Loyal customer group is mainly spontaneous, maybe due to an intrinsic motivation of such users. Hesitant users appear to be more influenced by the network effects arising from the size of the active user-base. There seems to be a strong influence of network effects for users leaving the platform, which suggests that the social aspect of the game is relevant for most users.

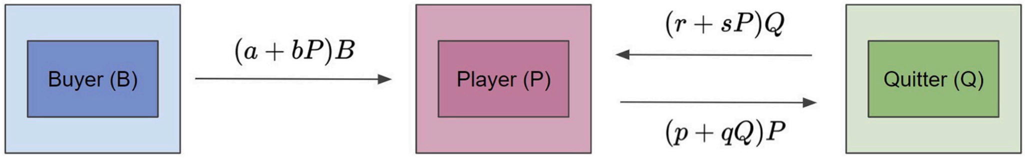

Fig. 2. Compartmental diagram of the BPQ model.

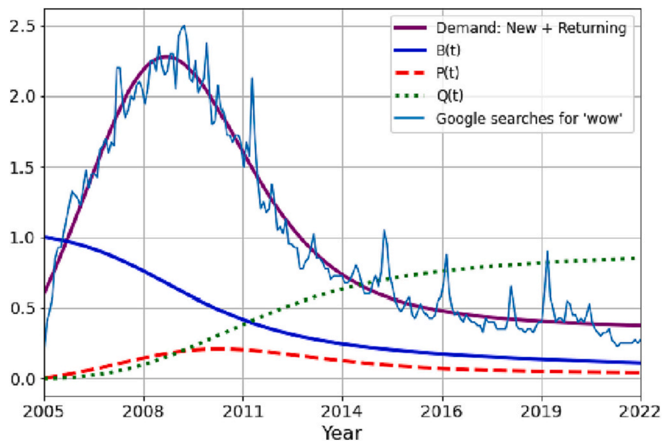

Fig. 3. Solutions of the BPQ model whose normalized demand fits best the number of Google Searches for 'wow'. The y axis shows the population of the compartments as a fraction of the total, and the demand is normalized so that the area under the curve is 1 (total number of users = 1). The resulting values of the fit are $a = 0.58$, $b = 16$, $p = 8.7$, $q = 4.1$, $r = 0.34$ and $s = 1.3$, following the naming convention from Fig. 2.

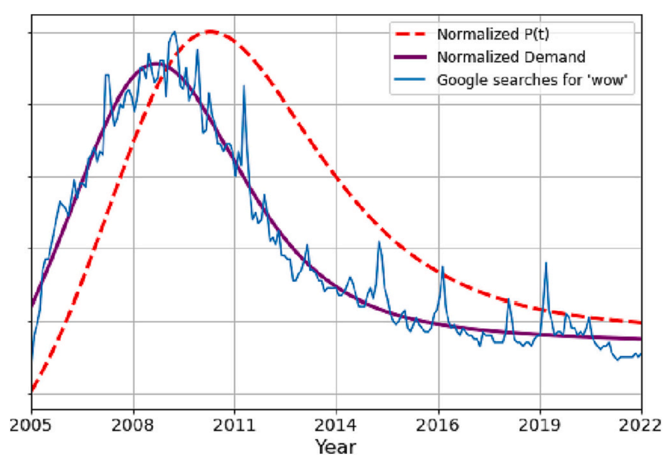

Fig. 4. Time evolution of the user-base of World of Warcraft as described by the BPQ model using Google Trends data as a proxy for the demand. The data had been re-scaled to portray better the offset between maximum demand and maximum user-base.

In this scenario, there is a conceptual advantage to the PHLoQui model. In the BPQ model, the fact that the game keeps a user-base after the initial surge is due to re-adoption, as explained in (Øverby and Audestad, 2021a). The population reaches an equilibrium where the users that leave the game and the ones that join it again are the same, leaving the net in-game population constant. In the PHLoQui model, the stable final state is due to a group of users that play it regularly, without the requirement of a dynamical exchange of users from two categories.

4.2.3. Facebook

Let us study the case of Facebook with the PHLoQui model. The solutions from Fig. 9 resemble a lot the results from Fig. 5. It is easy to see if we compare the *Total Users* curve in Fig. 9 to the *P*(t) curve in Fig. 5. In this case, both models offer a sensible description of the evolution of the user-base of Facebook. However, the PHLoQui model suggests additionally that, following its description, most of the customers are Loyal, in the sense that people do not usually delete their accounts, and keep using Facebook to some extent, thus explaining the great size of the social network.

If we take a closer look at the quitters, as we did with the BPQ model, we observe a similar behaviour: there are few Quitters but the numbers increase with time. This is shown in Fig. 10.

Let us take a detailed look now at the parameters resulting from the fit (Table 1), in order to gather more information about the process. The results are quite logical. First, we observe that people join this social network mainly influenced by other people having joined the network already, as $b > a$ and $d > c$. These strong network effects are characteristic of this kind of service. Moreover, we see that the group that joins Facebook with the highest presence of innovators are the Loyal customers. Although we had not been able to prove it, we argue that this is also reasonable, as it seems more likely that someone will stay on the service if they joined it because of personal/independent reasons, like the usefulness of its features, rather than just imitating others' behaviour. Finally, we see that it is more likely that people stop using Facebook due to personal or external reasons, rather than because other people stopped using it. In fact, although *Peer Pressure* is one important reason, most of the reasons provided in the literature (Hong and Oh, 2020) could be considered as personal or independent of the number of non-users. These results arise just from one input, which is the number of Google Searches for the keyword 'facebook', treated as the demand. No conditions (apart from being non-negative) were imposed on the parameters.

5. Discussion and conclusions

Throughout this study we have presented a shift in perspective regarding the use of publicly available Google Trends data for studying market evolution. Mainly, this means considering the normalized number of Google Searches as the demand for a product, for it represents a measure of the evolution of the interest on a product or service. We applied this concept using compartmental modeling.

After a brief overview of existing literature on Google Trends data (in general and as a tool for studying demand) and of compartmental methods (specifically for digital economics and market modeling), we described the basic methodology used in this study for implementing Google Trends data as the demand in compartmental models. We then presented two cases of different services (World of Warcraft and Facebook) whose temporal evolution had been analyzed using two different compartmental models, the BPQ model (Øverby and Audestad, 2021a) and a new model introduced in this study, the PHLoQui model.

The results we obtained were satisfactory in the sense that, with our interpretation of the data from Google Trends, both models were capable of replicating the key features of the evolution of both services, in relative agreement with the real data. This would not have been possible if the previous interpretation, considering this data as the number of users as done in (Cannarella and Spechler, 2014), had been used.

We found, after fitting the demand to the number of Google searches

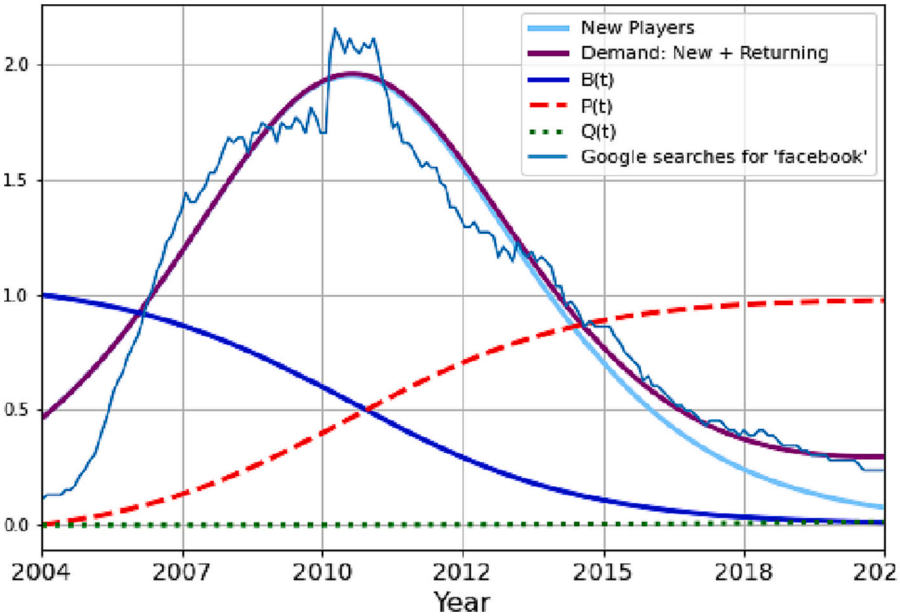

Fig. 5. Solutions of the BPQ model whose normalized demand fits best the number of Google Searches for 'facebook'. The y axis shows the population of the compartments as a fraction of the total, and the demand is normalized so that the area under the curve is 1 (total number of users = 1). The resulting values of the fit are $a = 0.46$, $b = 6.9$, $p = 0.016$, $q = 18$, $r = 4.0$ and $s = 12$, following the naming convention from Fig. 2.

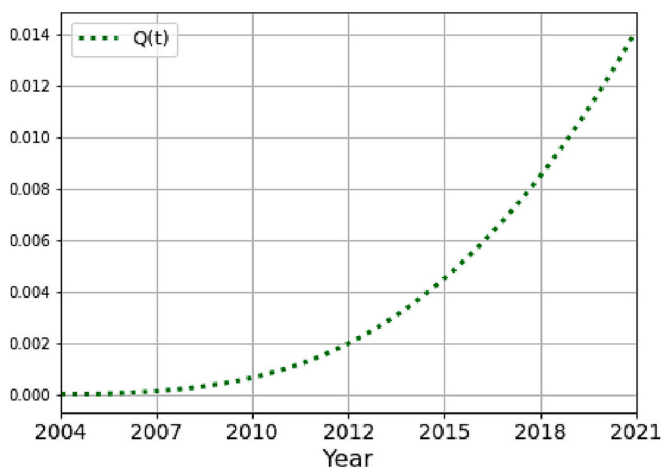

Fig. 6. Zoom of the *Quitters* compartment population evolution from Fig. 5.

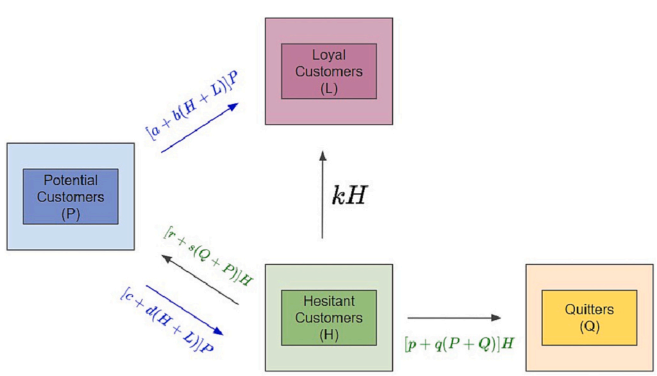

Fig. 7. Compartmental diagram of the PHLoQui model. The incoming customers flows marked with blue color represent the demand, the green ones represent customers exiting the user-base and the black flow represents the transition between Hesitant and Loyal customers.

for the specific keyword 'wow', that the MMO World of Warcraft reached a peak number of users at a time later than the maximum demand, and has been mostly declining ever since. This is in good agreement with the real data. We also have been able to describe the current situation of apparently approaching saturation of the user-base of Facebook, without any decline. The evolution of the user-base also seems compatible with said real case. We finally analyzed the parameters resulting from the PHLoQui model and concluded that the results fulfilled our expectations.

5.1. Research implications

With this research we add the emerging body of literature on modeling and forecasting the time evolution of digital platforms, enriching the current research, where applications of compartmental methods are still a recent area of study. We also respond to an issue suggested in (Øverby and Audestad, 2019), where the lack of data is outlined as a problem for studying the evolution of services such as video games.

Previous studies like (Øverby et al., 2023) have focused on the usefulness of compartmental methods for modeling digital economies, presenting several scenarios where their application proves beneficial. However, these studies are mostly theoretical, and "comparing theory and empirical results" (Øverby et al., 2023) is left for future research. Our study focuses on the first step of this future research: obtaining a source for empirical data that would enable researchers in this field to perform new case studies and circumvent the scarcity of data. Our analysis highlights the importance of trends for accurately capturing early signals in the evolution of digital platforms. Doing so, it also opens opportunities for understanding specific events that prompt decline, or identifying the impact that new features or announcements around digital platforms have on user retention.

More concretely, we show how the open access tool Google Trends can be used as a valuable source of input data that, in combination with dynamic market models, can provide insights into future scenarios of user-base evolution. Our approach provides a new application of the interpretation of Google Trends data as the demand for a digital product or service, which has proven capable of replicating real behaviour of user-bases. This means that the models developed here can capture the

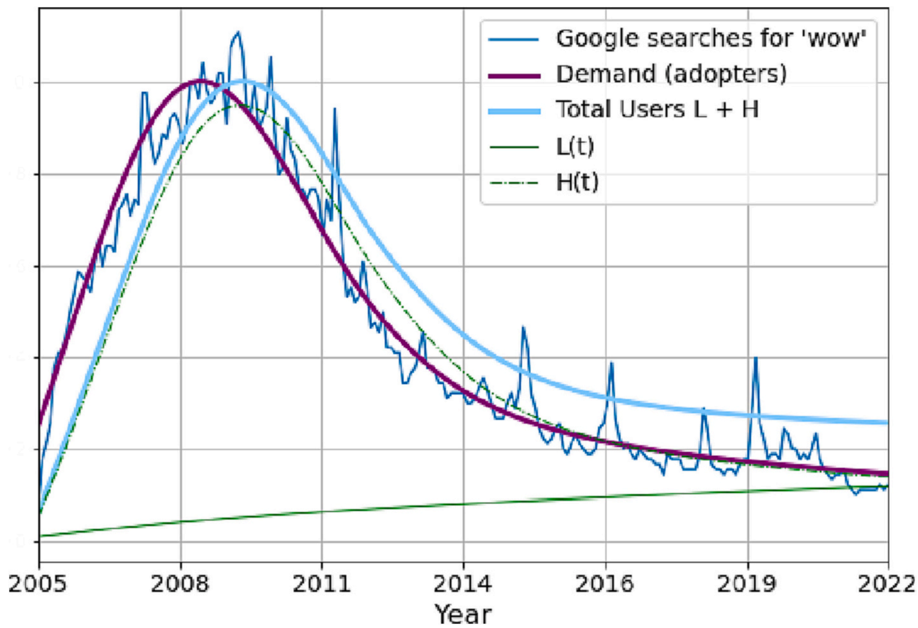

Fig. 8. Time evolution of the user-base (customers: Hesitant, Loyal and Total) of World of Warcraft as described by the PHLoQui model using Google Trends data as a proxy for the demand. The data had been re-scaled to portray better the offset between maximum demand and maximum user-base. The resulting values of the fit are $a = 0.019$, $b = 0.00014$, $c = 0.38$, $d = 29$, $r = 0.0021$, $s = 8.0$, $p = 0.00034$, $q = 18$ and $k = 0.00062$, following the naming convention from Fig. 7.

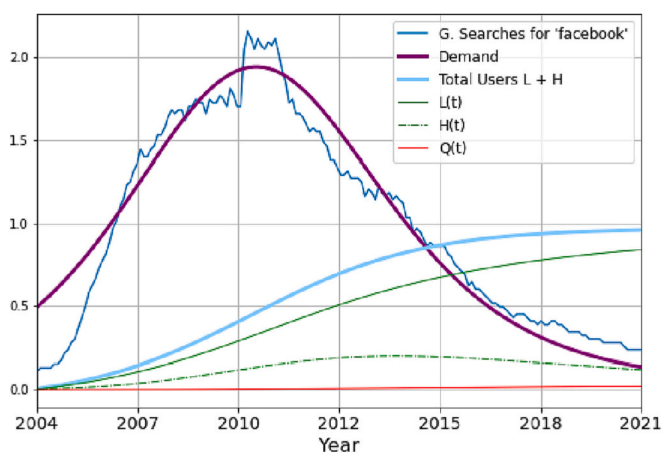

Fig. 9. Solutions of the PHLoQui model whose normalized demand fits best the number of Google Searches for 'facebook'. The y axis shows the population of the compartments as a fraction of the total, and the demand is normalized so that the area under the curve is 1 (total number of users = 1).

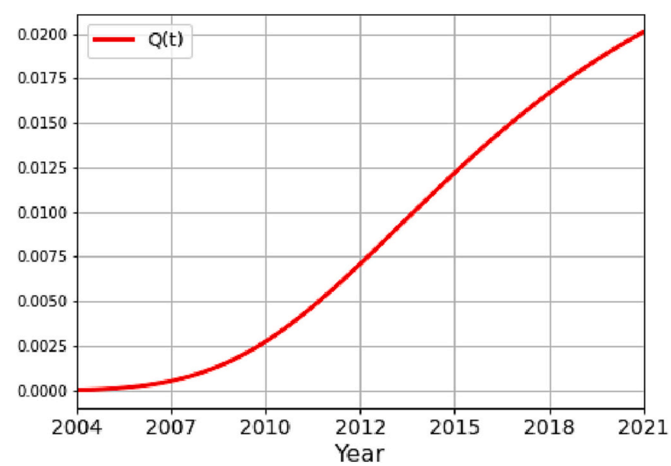

Fig. 10. Zoom of the *Quitters* compartment population evolution from Fig. 9.

basic underlying dynamics of the user-bases of digital platforms. For this reason, they could be used to identify early signs of changes (either increases or decreases) in the number of users, potentially helping to avoid negative consequences of delayed action.

One of the models used in this paper, the PHLoQui model, has been designed as a tool for interpretation of historical demand data. This model is able to capture scenarios where, in the long term, some services are able to maintain a small user base (even if many users had left). In this model, those users are called Loyal users. This is an advantage of the model: while previous models like the BPQ model can reproduce similar cases, the small final user base stems from a continuous exchange between users that join and leave the service (a dynamic exchange of users). The PHLoQui model can be used, therefore, to account for users that are loyal to the service and constitute the final user base, providing additional insights into the nature and development of digital platforms.

A greater understanding of the temporal evolution of digital platforms helps answering questions such as why and when some services fail, what are the conditions for a product to be successful and how to increase market penetration of a product. Further research is needed in order to better address these questions. In addition to deepening our perspective, the methodology proposed enables further the use of an open access tool in a context where freely available data is scarce. In addition, smaller time-frame effects of increasing or declining searches

Table 1
Parameters resulting from fitting the normalized demand of the PHLoQui model to the number of Google Searches for the keyword 'facebook'. For the meaning of the parameters, refer to Fig. 7.

Flow	Innovators	Imitators
$P \to L$	$a = 0.42$	$b = 3.4$
$P \to H$	$c = 0.037$	$d = 3.4$
$H \to Q$	$p = 0.15$	$q = 0.046$
$H \to P$	$r = 0.37$	$s = 0.12$
$H \to L$	$k = 2.0$	–

can be cross-linked to other online information such as news events, twitter trends, and other announcements to better understand what motivates users to adopt, continue or discontinue using digital platforms.

In the era of Artificial Intelligence it may seem that the models presented in this paper are oversimplifications with little application in real cases. However, as methods that involve Artificial Intelligence are often regarded as "Black Boxes" (Quinn et al., 2022), these simple models can, in reality, provide deeper insights into real processes as they offer a clear and evident description. Thus, one impact that this paper could have on current research is showing a simpler, yet sometimes more insightful, alternative to Artificial Intelligence methods for forecasting the evolution of digital markets.

5.2. Practical implications

A possible application of better understanding the evolution of a digital platform at an early phase is assessing its success or failure. This could help to describe the factors and the conditions that lead for the termination of a service. This knowledge would be then useful for determining the point of its life cycle that a service is currently at, helping managers (both in the private and the public sector) to decide when a service should be discontinued. In terms of environmental and economic sustainability, this would mean the cessation of resource expenditure on a service that no longer provides value, or investing more on a service projected to retain a reasonable share of loyal users. However, the use of this type of data must always be approached carefully as predictions are not 100 % guaranteed (the same happens for any predictive model), and overconfidence in this context could have negative economic, social, and environmental consequences. For example, a potentially helpful service could be terminated prematurely because of failure projections in the early stages.

For smaller businesses, using these tools can add value in terms of a preliminary market study, providing an inexpensive and accessible way of analyzing the approximate evolution of the interest of the population on a product. This would allow those businesses to take decisions to maximize the attention they receive, as well as to manage future expectations without over-investing in unpopular products. This approach can be further utilized by stratifying or segmenting the types of searches based on geographical area, age group and other dimensions in order to isolate the effect that digital platform usage will likely have to specific population segments.

Given the popularity of Google Search, the methods presented in this study provide a methodology for uncovering potential future scenarios for the user-base of a service. Using Google Trends data as an input for these compartmental models, one could prevent potential infrastructure failures due to a sudden increase in demand by understanding that the prospects of growth of a service. Also, if the demand data (processed with these models) indicates a likely reduction of the user base in the near future, user retention measures could be implemented in time to slow down the decrease. Additionally, models such as the PHLoQui model that aim to portray the proportion of distinct groups of users over time, are helpful to understand the composition of the user-base, and thus reveal for example if any action is needed for increasing the loyalty of the users of a service.

Finally, it is important to note that these models are not a complete depiction of reality, but they act as a useful simplification that shares some important characteristics with real markets. Indeed, as we have seen in *Sec.* 4, the models are able to provide interesting insights into real markets. However, the aim of the models is not to provide a specific number for the number of users of a service in the future, but to show potential trends in adoption or quitting that may have important consequences, based on an input of freely available data.

5.3. Limitations and future research

One limitation of this research is that we had not had access to real data for verifying the robustness of the models presented. By comparing the results of the model to real detailed data of user-base evolution, we would be able to assess to which extent our models can be used for gaining knowledge about the services at study, and in general about the factors that affect the life cycle of digital services. This, however, is left for future research.

In the examples presented in this research, we treat the parameters as values that we fit to data. We had not discussed in depth the factors that influence the values of those parameters. Their meaning and how businesses' decisions affect their value is a limitation of this study and is left for future research.

Finally, follow-up research is needed for exploring how to apply this perspective on Google Trends data to other contexts, with other types of models and to other products or services, to further verify and assess its usefulness and validity, as the aim of this study is mainly presenting the new perspective.

CRediT authorship contribution statement

Gabriel Andy Szalkowski: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Patrick Mikalef:** Conceptualization, Writing – original draft, Writing – review & editing, Investigation, Supervision.

Data availability

Data will be made available on request.

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Gabriel Andy Szalkowski is a PhD candidate at the Norwegian University of Science and Technology, in the PERSEUS doctoral programme. As a part of the Department of Information Security and Communication Technology his research focuses on Digital Economics and Sustainability, a highly cross-disciplinary project combining knowledge from economics, business and technology with a strong focus on mathematical modeling. He received his B.Sc. in Physics and his M.Sc. in Advanced Theoretical Physics from the University of Valencia, Spain.

Patrick Mikalef is a Professor in Data Science and Information Systems at the Department of Computer Science. In the past, he has been a Marie Sklodowska-Curie post-doctoral research fellow working on the research project "Competitive Advantage for the Data-driven Enterprise" (CADENT). He received his B.Sc. in Informatics from the Ionian University, his M.Sc. in Business Informatics for Utrecht University, and his Ph.D. in IT Strategy from the Ionian University. His research interests focus on the strategic use of information systems and IT-business value in turbulent environments. He has published work in international conferences and peer-reviewed journals including the Journal of Business Research, British Journal of Management, Information and Management, Industrial Management & Data Systems, and Information Systems and e-Business Management.