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Strategic Adoption of Immersive Technologies in Cultural Heritage and Tourism

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Abstract

Immersive technologies are at a crossroads, with many actors pondering their adoption. The cultural and tourism industries are particularly impacted, facing significant pressure to make decisions that could shape their future landscapes. Stakeholders' perceptions play a crucial role in this process, influencing the speed and extent of technology adoption. As immersive technologies promise to revolutionize experiences, stakeholders in these sectors need to evaluate the benefits and challenges of embracing such innovations. The current choices will likely determine the trajectory of cultural preservation and tourism enhancement, potentially transforming how we engage with history, art, and travel. Starting from a decomposition of stakeholders' perceptions into principal components using Q-methodology, this article employs an evolutionary game model to forecast the possible scenarios and highlight potential decision-making trajectories. The proposed approach highlights how evolutionary dynamics identify a dominant strategy that emerges in the long-term.

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1 Introduction

Immersive technologies are at a pivotal juncture, as numerous sectors contemplate their adoption and potential applications ([21]). Among these sectors, cultural and tourism industries are particularly impacted, facing significant pressure to decide whether and how to integrate these immersive technologies ([15], [34], [30], [26], [36]). The rapid development of immersive technologies presents both opportunities and challenges for these sectors. Museums, galleries, and heritage sites can harness these immersive technologies to create engaging, interactive experiences that attract new audiences and deepen visitor engagement ([32]).

For the tourism industry in particular, immersive technologies can offer virtual tours, enhancing marketing efforts and providing unique experiences to potential travellers ([34], [16]). Immersive technologies promise to revolutionize experiences by offering unprecedented levels of engagement and interaction ([33], [19], [3]). In the cultural sector, museums and galleries could use immersive technologies to create more interactive and informative exhibits, enhancing visitors' understanding and enjoyment of art and history ([11]).

Similarly, the tourism industry could leverage these technologies to offer virtual tours of landmarks and destinations, allowing potential travellers to explore places before visiting in person ([20]). However, the integration of these technologies is not without challenges. High costs, technical complexities, and concerns about accessibility and inclusivity must be addressed. Stakeholders need to carefully consider these factors and weigh them against the potential benefits. Stakeholders' perceptions play a crucial role in this decision-making process, shaping the pace and extent of adoption ([4], [8]). Consequently, the cultural and tourism industries are at a critical juncture, experiencing significant pressure to make decisions that could shape their future landscapes ([1]).

Our contribution aims to forecast the evolution of stakeholders perceptions in relation to immersive technologies adoption in culture heritage and tourism sectors. In order to achieve this result we rely on evolution game theory and on recent studies about perceptions analysis ([5]).

Using this combined approach, our study allowed us to navigate the complexities of immersive technology adoption in culture heritage and tourism sectors and highlights how strategies can become dominant through a progressive selection. Our results help to clarify the likely paths of immersive technology adoption and, by understanding these dynamics, we are able to add an important piece to the understanding of economic dynamics that revolve around these technologies. Furthermore, to our knowledge, this is the first example of a combined approach between perception analysis and evolutionary game theory that could open interesting new lines of research on several fronts.

The paper is organized as follows: in section 2 we briefly describe immersive technologies and their role within the tourism/cultural sector; in section 3 we recall the results obtained by applying the Q-methodology in the evaluation of the different perceptions of stakeholders about the adoption of immersive technologies; in section 4 we introduce the replicative dynamics typical of evolutionary game theory; in section 5 we discuss the results obtained by our combined approach and, finally, in section 6 we illustrate the main conclusions of our work.

2 Immersive technologies

Immersive technologies are a broad spectrum of advanced digital tools and systems that create or enhance the sense of physical presence in a virtual or simulated environment. They represent the intersection of the physical and digital worlds, where users can interact with and experience environments that feel as though they are a part of them, rather than merely observing them. These technologies leverage a combination of hardware and software to generate environments that can be entirely artificial or an augmentation of the real world.

One of the most recognized forms of immersive technology is Virtual Reality (VR). VR is a fully immersive experience where the user is placed in a completely digital environment. This is achieved through devices such as headsets, which cover the user's field of vision and often include headphones to block out real-world sensory input. In VR, users are transported to a different world, one where they can look around in 360 degrees, move within the space, and interact with objects as if they were physically present. The key characteristic of VR is that it creates an entirely new reality for the user, detaching them from their physical surroundings.

In contrast, Augmented Reality (AR) enhances the real world by overlaying digital information onto the physical environment. Unlike VR, AR does not create a new world but enriches the existing one with additional layers of information. This can be achieved through devices like smartphones, tablets, or AR glasses that project digital elements such as images, sounds, or data over the user's view of the real world. For example, AR might allow a person to see directions on the road in front of them, or visualize how a piece of furniture would look in their living room before purchasing it.

Mixed Reality (MR) is another form of immersive technology that blends aspects of both VR and AR. In MR, digital objects are not just overlaid on the real world but are anchored to it and interact with it in real time. This means that a virtual object in MR can be occluded by real-world objects, or respond to changes in lighting and environment. MR creates a seamless integration between the physical and digital worlds, where both can coexist and interact with each other in meaningful ways. A key example of MR is Microsoft's HoloLens, a device that allows users to see and interact with holograms within their real environment.

Lastly, Extended Reality (XR) is a term that encompasses all forms of immersive technologies, including VR, AR, and MR. XR serves as a broad umbrella under which these technologies fall, representing the entire spectrum of digitally mediated experiences. XR is often used to describe the evolving landscape of immersive technologies as they continue to develop and converge, pushing the boundaries of what is possible in digital experiences.

Despite their similarities, these technologies offer distinct experiences. VR fully immerses users in a new world, AR enhances the real world with digital overlays, MR creates a blend of real and virtual interactions, and XR encompasses all these forms, representing the future of immersive digital experiences. Each has its own set of use cases, advantages, and challenges, making them suitable for different applications across industries such as gaming, education, healthcare, and more.

3 Stakeholders' perceptions towards immersive technologies: a Q-meth approach

Stakeholders' perceptions are pivotal in determining the speed and extent of technology adoption, particularly in the integration of immersive technologies within various sectors ([5]). In the cultural and tourism industries, these perceptions can significantly influence whether these technologies are embraced or resisted. Stakeholders include a diverse group—ranging from industry leaders and policymakers to consumers and technology developers—each bringing unique perspectives and concerns ([8]). For instance, cultural institutions like museums may perceive AR and VR as valuable tools for enhancing visitor engagement and education, leading to a more enthusiastic adoption. Conversely, concerns about high implementation costs, technical challenges, and potential disruptions to traditional experiences might slow down their integration ([13]). Similarly, in the tourism sector, stakeholders might view immersive technologies as revolutionary for marketing and virtual exploration, driving quicker adoption. Yet, scepticism about their long-term value and the readiness of the market could temper this enthusiasm ([11], [14]).

3.1 Q-meth approach

The Q-methodology starts from the hypothesis of being able to frame the evaluation of single individuals as a weighted average between independent points of view that are standard for almost everyone ([28]). Starting from this assumption, through a revised version of the Q-methodology ([9]), it is possible to hypothesize that the perception of the usefulness of a specific combination of characteristics (in the Lancaster style ([17], [18])) can also be broken down into a weighting of different points of view that can attribute different importance to those characteristics. Through Q-methodology, stakeholders' diverse viewpoints can be organized and categorized, providing valuable insights for decision-making processes ([9]). This method enables a deeper understanding of stakeholders' perspectives, uncovering underlying patterns and priorities. Furthermore, imagining a form of adaptation through a rational evaluation, we can hypothesize an evolutionary competition with a progressive selection of choices towards the one perceived as the most useful at the end.

Recent advancements in Q-methodology allow for the identification of key factors shaping stakeholder perceptions ([5]). The procedure followed to implement the q-meth approach is described in detail in [5], here we will limit ourselves to using the main results for the purposes of this article. The study focused on understanding how different tourism stakeholders, such as managers of attractions like archaeological parks, museums, and nature reserves, perceive and integrate metaverse tools into their strategies. Key findings indicate that stakeholders have varied preferences and levels of awareness regarding the use of metaverse technologies. Some are fully aware and view these tools as beneficial, while others lack sufficient knowledge and remain hesitant. This variance suggests that the tourism sector is still in a transitional phase concerning the adoption of immersive technologies.

3.1.1 Q-meth results summary

In this paper, we use the results obtained in [5] to understand which possible future scenarios might unfold. Their analysis focus on the following four main characteristics that concur with the definition of best tourism marketing strategy:

- Main target;
- Main content;
- Principal tool (or media channel);
- Preferred financial scheme (resources).

Referring to the first item, it was split into two options: domestic and international tourists. Regarding the second one, two possibilities are considered: content purely for recreational entertainment vs. content aimed at cultural growth. The options for media channel to develop attractiveness are: traditional advertising tools as standard media (TV or print advertising), consolidated digital tools (Internet/social-media advertising), or advanced digital tools such as Metaverse (AR, VR). Lastly, the main actors implementing the strategy should be: public resources, private resources, or a mixed public/private resource.
So, participants were provided with different levels of the four variables: *Target, Content, Tool, and Resource.*

Target	Content	Tool	Resource
Domestic (D)	Recreational (R)	Traditional (T)	Public (Pu)
International (I)	Cultural (C)	Standard digital (S)	Private (Pr)
		Advanced digital (A)	Mixed (PP)

Table 1: Available options for each of the dimensions that contribute to forming the possible strategies.

A typical statement had the following form:

*For me, the best strategy to increase the tourist attraction of the place where I live is the one that aims at an **international tourist target**, based on a proposal of purely **recreational content** that uses **traditional tools (such as TV or print advertising)** and funded by **public economic resources**.*

Combining the different levels of the four variables, we obtain thirty-six statements (it's possible identified the above statement by the code: $I.R.T.Pu$ and so on for the other statements).
Following the directions of the Q-sort methodology process ([31]), [5] focused on 20 stakeholders of different nature and with different roles. As a result of the Q-sort survey carried out, for each of the 36 combinations/statements about the best destination marketing strategy, they obtained 20 evaluations (one from each of the participants) ranging from -5 (in case they consider it the one with which they most disagree) to 5 (in the case consider it the one with which they are most in agreement). In a certain sense, we can imagine that agreeing or disagreeing with individual strategies could represent their perception about the usefulness of each of the strategies. In Figure 1, they have reported the box-plot of the values obtained for each statement they have recorded. Following the criterion proposed by Zabala ([35]), it is possible to "flag" each of the participants with respect to the top five Q-factors based on loadings (Table 2). The Zabala's R-package ([35]) provides also a simulation of the answers from the various points of view of the Q-factors by assigning a factored score to each of the statements following the distribution of the values (from -5 to +5); these are listed in Table 3.

Stakeholder	Q-Factor-1	Q-Factor-2	Q-Factor-3	Q-Factor-4	Q-Factor-5
STK1	**0,84**	0,17	0,07	-0,12	0,27
STK2	0,67	-0,18	0,01	0,15	0,64
STK3	0,07	0,53	0,31	**0,7**	-0,08
STK4	**0,79**	-0,39	-0,2	0,06	-0,14
STK5	**0,67**	-0,16	0,13	0,08	0,25
STK6	**0,88**	0	0,06	-0,13	-0,05
STK7	**0,85**	0,04	0,04	-0,04	-0,12
STK8	**0,68**	-0,15	0,1	0	0,65
STK9	-0,29	0,13	-0,28	0,29	**-0,66**
STK10	0,02	0,1	**0,95**	0,05	0,15
STK11	**0,61**	-0,48	-0,29	-0,06	-0,13
STK12	0,02	0,1	**0,95**	0,05	0,15
STK13	0,22	-0,1	0,12	**0,73**	0,26
STK14	-0,09	0,38	0,19	**0,86**	-0,14
STK15	-0,03	0,13	**-0,6**	-0,18	0,46
STK16	-0,05	**0,81**	0,18	0,05	-0,08
STK17	0,36	0,08	0,19	**-0,76**	0,04
STK18	-0,09	**-0,69**	0,12	-0,18	0,06
STK19	0,24	0,01	0	-0,18	**-0,87**
STK20	-0,31	**0,81**	-0,01	-0,05	-0,03

Table 2: Loading values of each participant; highlighted the values used to flag stakeholders on Q-factors ([5]). It can assign 7 stakeholder to Q-Factor1 (35%), 3 to Q-Factorr-2 (15%), 3 to Q-Factor-3 (15%), 4 to Q-Factor-4 (20%) and 2 to Q-Factor-5 (10%). One stakeholder has not been assigned to any Q-Factor.

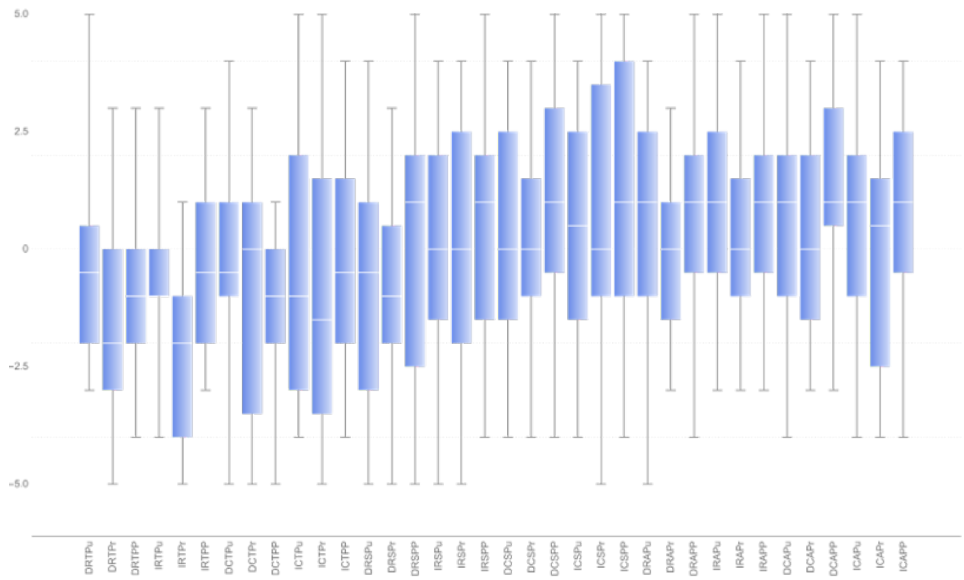


Figure 1: Box-plot of the distributions of the values obtained for each statement ([5]).

Referring to Roger's model on innovation adoption ([25]), they identify **Q-factor 1** as the *Early Majority adopters* category. Conversely, **Q-factor 5**, perceiving the Metaverse as least significant, aligns with *Laggards*, slowest to adopt due to perceived high costs or risks, preferring community support over individual burden. **Q-factors 3 and 4** may represent the *Late Majority*, cautious about innovation and adopting after average participants. Q-factor 4 specifically prioritizes content over tools, evaluating the Metaverse on its cultural content delivery. Finally, **Q-factor 2** aligns with the perspectives of *Innovators and Early Adopters*.

Q-factor 1 emerges as the primary viewpoint, explaining the most variance in the sample and endorsed by the largest participant group. Participants identified with Q-factor 1 play a pivotal role in shaping tourist destination promotion strategies. Notably, preferences between "Standard" and "Advanced" digital tools lack clarity as distinct entities. Overall, the Advanced digital tools are slightly less favoured than social options. Despite Q-factor 1 participants having the highest immersive technologies knowledge, they do not perceive a positive marginal utility compared to standard tools, which remain preferred.

Strategies	$zscore^{Q_1}$	$zscore^{Q_2}$	$zscore^{Q_3}$	$zscore^{Q_4}$	$zscore^{Q_5}$
D.R.T.Pu.	-3	-1	-2	2	1
D.R.T.Pr.	-2	-2	-2	-2	-3
D.R.T.PP.	-3	1	-2	1	0
I.R.T.Pu.	-1	0	-1	3	1
I.R.T.Pr.	-4	-2	0	-2	-1
I.R.T.PP.	-2	2	0	0	-1
D.C.T.Pu.	-1	0	4	-1	0
D.C.T.Pr.	-5	-3	3	0	-2
D.C.T.PP.	-2	3	-1	-1	-1
I.C.T.Pu.	-3	0	5	3	0
I.C.T.Pr.	-4	-4	3	-3	0
I.C.T.PP.	-2	1	2	2	-2
D.R.S.Pu.	0	2	-5	-3	2
D.R.S.Pr.	-1	-3	-3	0	1
D.R.S.PP.	2	4	-4	1	3
I.R.S.Pu.	-1	1	-3	-5	4
I.R.S.Pr.	2	-2	-3	1	3
I.R.S.PP.	2	3	-4	0	2
D.C.S.Pu.	3	2	0	-4	-1
D.C.S.Pr.	3	-1	1	0	2
D.C.S.PP.	3	5	0	0	2
I.C.S.Pu.	1	1	1	-2	3
I.C.S.Pr.	4	-1	0	2	5
I.C.S.PP.	1	3	0	-1	4
D.R.A.Pu.	0	-1	1	4	-3
D.R.A.Pr.	0	-2	-2	-1	0
D.R.A.PP.	5	4	-1	1	1
I.R.A.Pu.	-1	-1	2	5	-2
I.R.A.Pr.	0	-4	-1	-3	-3
I.R.A.PP.	2	2	-1	1	-5
D.C.A.Pu.	4	0	2	2	-4
D.C.A.Pr.	0	-5	2	-2	-2
D.C.A.PP.	1	0	1	3	0
I.C.A.Pu.	0	0	4	-1	-1
I.C.A.Pr.	1	-3	1	-4	-4
I.C.A.PP.	1	1	3	4	1

Table 3: Q-factor score for each statement obtained by Zabala's R-package ([35], [5]).

Under the assumptions of the Q-methodology and proposed statement configuration, we can associate the scores of Table 3 the relative utility values that each Q-factor assigns to each of the 36 proposed strategies. These findings illuminate the current immersive technologies penetration in tourism and stakeholder perceptions of their competitive advantages in destination attractiveness. The competition among the various Q-factors opens up several scenarios that trace different trajectories regarding the implementation of immersive technologies in the near future. The game that will decide which Q-factor will prevail and, consequently, which final strategy will be preferred is difficult to decipher; what we can do is try to imagine the evolution of this game.

4 Replicator dynamics and evolutionary game-theory model

Game theory is the part of mathematics that models strategic behavior ([2]). A symmetric game is defined by m players (*individuals*), that have to choose among n *strategies* $\mathbf{str}_i$, $i = 1, \ldots, n$, and as a result each one receive a certain *pay-off*: *each player acts to maximize his pay-off function.* A set of strategies in which no rational player has incentives to deviate from his strategy is called a *Nash equilibrium* ([10]).

Classical game theory primarily deals with one-time interactions among players who act perfectly rationally, fully aware of all the details of the game. In contrast, *evolutionary game theory* considers games that repeat over time and involve players chosen randomly from a sufficiently large population. Evolutionary game theory was initially formulated by biologists studying conflicts among animals and the theory of evolution. In this context, some evolutionary processes modify the types of behavior and their distribution within the population ([27]).

While classical game theory assumes that players are perfectly informed and rational, evolutionary game theory recognizes that interactions occur in a dynamic context, with individuals who can adapt and change strategies over time. This approach considers how game strategies spread and stabilize in a population, influenced by evolutionary mechanisms such as natural selection and mutation. Consequently, evolutionary game theory offers a more realistic perspective on how behaviours evolve and adapt in natural environments, as well as how these processes can be applied to social and economic contexts, providing a deeper understanding of the dynamics of interaction among individuals.

In evolutionary game theory, it is customary to replace the rationality assumption with a given dynamics. In particular, a population of individuals of n different types where each type adopts one of the strategies $\mathbf{str}_i$, $i = 1, \ldots, n$ is considered.

The fraction of individuals of type i at time $t \geq 0$ is given by $x_i(t) \in [0, 1]$, and the *state* of the population is given by $\mathbf{x}(t) = (x_1(t), \ldots, x_n(t)) \in S^{n-1} := \{\mathbf{z} \in \mathbb{R}^n_+, \sum_{i=1}^n z_i = 1\}$, the $n-1$-dimensional *simplex*, for all $t \geq 0$.

Payoff functions, often referred to as *fitness* in literature ([7]), are smooth functions denoted as $\psi_i : S^{i-1} \to \mathbb{R}$ for $i = 1, \ldots, n$. Specifically, at a given state $\mathbf{x}$, individuals of type i have a fitness represented by $\psi_i(\mathbf{x})$.

The state of the population evolves according to a specified dynamic, with the *replicator dynamics* being the most widely recognized ([29]).

4.1 Replicator dynamics

Replicator dynamics is a fundamental concept in evolutionary game theory, providing a mathematical framework to model how the composition of strategies in a population evolves over time ([22]). Rooted in Darwinian principles of natural selection, replicator dynamics posits that strategies yielding higher payoffs, or fitness, increase in frequency, while those with lower payoffs diminish ([27]). In more detail, the replicator equation illustrates that the growth rate of a strategy's frequency is proportional to the difference between the strategy's payoff and the average payoff of the population. If a particular strategy's payoff exceeds the population average, its frequency will grow, promoting the spread of advantageous traits. Conversely, if the payoff is below average, the strategy's prevalence will decline. This process leads to the natural selection of optimal strategies over time ([12]).

This dynamic is described by differential equations that capture the rate of change in the proportion of each strategy within the population:

$$\dot{x}_i = x_i \left(\psi_i(\mathbf{x}) - \overline{\psi}(\mathbf{x}) \right), \tag{1}$$

where $\overline{\psi}(\mathbf{x}) := \sum_{i=1}^{n} x_i \psi_i(\mathbf{x})$ is the average pay-off.
In this case we have always considered symmetric conflicts, in the sense that all players are indistinguishable. Let us restrict ourselves to games between two different species, say X and Y, and always assume that the possible strategies are finite; moreover, let us assume that the two players facing each other always belong to different species.
Let $E_1, \ldots, E_n$ be the possible strategies for population X and $F_1, \ldots, F_m$ the possible strategies for population Y. We denote by x_i the frequency of E_i within X, and by y_j the frequency of F_j within Y; thus, the state x of population X will be a point in S_n, and the state y of population Y will be a point in S_m. If an individual using strategy E_i plays against an individual using strategy F_j, we call a_{ij} the payoff for the first player, and b_{ji} the payoff for the second; thus, the game is described by the payoff matrices $A = (a_{ij})$ and $B = (b_{ji})$.
The expressions $x^T Ay$ and $y^T Bx$ represent the average payoffs for populations X and Y respectively.
As we have done before, we can associate a system of differential equations with the game: we assume that the growth rate $\frac{\dot{x}_i}{x_i}$ of the frequency of strategy E_i is equal to the difference between the payoff $(Ay)_i$ and the average payoff $x^T Ay$. This, and the corresponding hypothesis for the growth rate of the frequency of strategy F_j, lead to the replication system

$$\dot{x}_i = x_i((Ay)_i - x^T Ay), \quad i = 1, \ldots, n \tag{2}$$

$$\dot{y}_j = y_j((Bx)_j - y^T Bx), \quad j = 1, \ldots, m \tag{3}$$

on the space $S_n \times S_m$ of all states for X and Y.
These differential equations can be solved simultaneously using numerical algorithms that allow the reconstruction of the temporal trends of the variables under study; however, to do this, it is necessary to set the initial conditions to start from. These conditions become crucial because the form of the differential equations is such that initial conditions with null values for some variables prevent them from evolving.

4.2 Strategies evolution in Stakeholder perspective

We can apply the general model to our case by schematizing the relationship of individual stakeholders who confront (compete with) the decisions of the

community in a general sense. Specifically, referring to what was proposed in [5], we can assume that each stakeholder prefers among the various Q-factors given the expected utility that a particular strategy imposed by the community will provide to him. From the community's perspective, the chosen strategy is the one that maximizes the expected utility for the collective.
For the population of stakeholders (X), the possible strategies are {Q-fact-1, Q-fact-2, Q-fact-3, Q-fact-4, Q-fact-5}, and the frequencies $x_{qi}(t)$ represent the fractions of the population that *align* with the various q-factors; $x_{qi}(t)$ at $t = 0$ will be determined by the number of stakeholders flagged for each Q-factor relative to the total sample (see Table 2).

	Q-fact-1	Q-fact-2	Q-fact-3	Q-fact-4	Q-fact-5
$x_{qi}(0)$	0.35	0.15	0.15	0.20	0.10

Table 4: Initial values for $x_{qi}(t = 0)$; the values have been calculated according to to the fraction of stakeholders assigned to the Q-factors (see Table 2).

On the other hand, for the community Y, the possible strategies correspond to the 36 combinations of the variables analysed indicated by the statements according to the coding as reported in Table 1. The frequencies y_i correspond to the fraction of stakeholders who assigned the highest value to the i-th combination during the q-sorting phase.
Regarding the $y_j(0)$, given that the number of stakeholders is less than the statements, this means that some $y_j(0)$ could be zero, blocking some evolution paths from the outset. To avoid this, we decided to generate for each of the 36 statements 30,000 random values based on a normal distribution with mean and sigma as shown in the Figure 1. The frequencies y_j at time 0 correspond to the fraction of the 30,000 sequences that assigned the highest value to the j-th combination. The obtained values are shown in Table 5 (the simulations were repeated multiple times to ensure the robustness of the results obtained).
Since the loadings of each stakeholder for the various Q-factors can assume a positive or negative value, we added an additional level by considering that for each Q-factor there are two possible strategies $-Q_i$ and $+Q_i$. In this case, for each Q-factor, the payoff matrix corresponds to a 2×36 matrix where in the first row the values correspond to the respective z-scores (as shown in Table 3) and in the second row to the same values with opposite signs.

D.R.T.Pu.	D.R.T.Pr.	D.R.T.PP.	I.R.T.Pu.	I.R.T.Pr.	I.R.T.PP.
0.0058	0.003	0.0010	0.0029	0.0002	0.0022
D.C.T.Pu.	D.C.T.Pr.	D.C.T.PP.	I.C.T.Pu.	I.C.T.Pr.	I.C.T.PP.
0.0073	0.0146	0.0007	0.0273	0.0224	0.0108
D.R.S.Pu.	D.R.S.Pr.	D.R.S.PP.	I.R.S.Pu.	I.R.S.Pr.	I.R.S.PP.
0.0129	0.0054	0.0630	0.0359	0.0317	0.0358
D.C.S.Pu.	D.C.S.Pr.	D.C.S.PP.	I.C.S.Pu.	I.C.S.Pr.	I.C.S.PP.
0.0314	0.0159	0.0707	0.0359	0.0833	0.0823
D.R.A.Pu.	D.R.A.Pr.	D.R.A.PP.	I.R.A.Pu.	I.R.A.Pr.	I.R.A.PP.
0.0382	0.0020	0.0442	0.0570	0.0131	0.0373
D.C.A.Pu.	D.C.A.Pr.	D.C.A.PP.	I.C.A.Pu.	I.C.A.Pr.	I.C.A.PP.
0.0391	0.0222	0.0505	0.0332	0.0285	0.0319

Table 5: Initial values for $y_i(t = 0)$; the values have been calculated according to the fraction of the 30,000 sequences that assigned the highest value to the j-th combination.

Considering that there are only two possible choices for each factor, we can refer to the frequencies of each $+Q_i$, z_{qi}, and write the replication equation as follows:

$$\dot{z_{qi}} = z_{qi}(1 - z_{qi})\Delta\psi^{Q_i}, \tag{4}$$

where $\Delta\psi^{Q_i} := \psi^{+Q_i} - \psi^{-Q_i} = 2 * \psi^{+Q_i}$.
ψ^{+Q_i} corresponds to the expected utility value for the i-th Q-factor from the weighted (by y_i) mix of strategies of Y.

$$\psi^{+Q_i} = \sum_j zscore_j^{Q_i} y_j, \tag{5}$$

where $zscore_j^{Q_i}$ represent the values of Table 3.
If ψ^{+Q_i} is positive, we say that $+Q_i$ dominates $-Q_i$ and that $-Q_i$ dominates $+Q_i$ otherwise. Note that $z_{qi}(t) \overset{t\to\infty}{\longrightarrow} 1$ in the first case and $z_{qi}(t) \overset{t\to\infty}{\longrightarrow} 0$ otherwise for all non-trivial initial conditions.
The values of $z_{qi}(t = 0)$, for each Q_i, refer to the fraction of stakeholders' positive loadings (see Table 2); in Table 6 we report the values obtained.

	Q-fact-1	Q-fact-2	Q-fact-3	Q-fact-4	Q-fact-5
$z_{qi}(0)$	0.39	0.33	0.39	0.28	0.28

Table 6: Initial values for $z_{qi}(t = 0)$; the values have been calculated according to the fraction of stakeholders' positive loadings (see Table 2).

The payoff matrix A of X depends on the z-score matrix and on the frequencies z_{qi} according to the following formula:

$$A := a_{ij} = zscore_j^{Q_i} * (2 * z_{qi} - 1) \tag{6}$$

Thus, for the x_{qi}, the following replication equations are obtained:

$$\dot{x_{qi}} = x_{qi}((Ay)_i - x^T Ay), \quad i = 1, \ldots, 5 \ (Qfactors) \tag{7}$$

Regarding Y, the payoff matrix B corresponds to the transpose of A; so for the y_i, the following replication equations are obtained:

$$\dot{y_j} = y_j((A^T x)_i - y^T A^T x), \quad j = 1, \ldots, 36 \tag{8}$$

Thus, we obtain a system of differential equations that includes equations (4), (7) and (8) which can be solved numerically, imposing the initial conditions at $t = 0$ as indicated in Table 4, 5, 6.

5 Results and discussion

As mentioned earlier, our analysis focused on solving the differential equations defined in (4), (7) and (8). Specifically, our system consists of 5 differential equations for $z_{qi}(t)$, 5 for $x_{qi}(t)$, and 36 for $y_i(t)$. In total, we have a system of 46 differential equations and 46 initial conditions provided by the tables 4, 6, 5. Our goal is to understand the temporal evolutions of variables $z_{qi}(t)$, $x_{qi}(t)$ and $y_i(t)$; this will allow us to determine whether the system evolves towards a solution where one factor dominates over the others (and with what sign), and consequently, which strategy will ultimately prevail.

To solve the system of differential equations, we leveraged the capabilities offered by Wolfram's Mathematica software, specifically utilizing the NDSolve function ([24]). NDSolve is a fundamental tool in Mathematica for the numerical solution of ordinary differential equations (ODEs) and partial differential

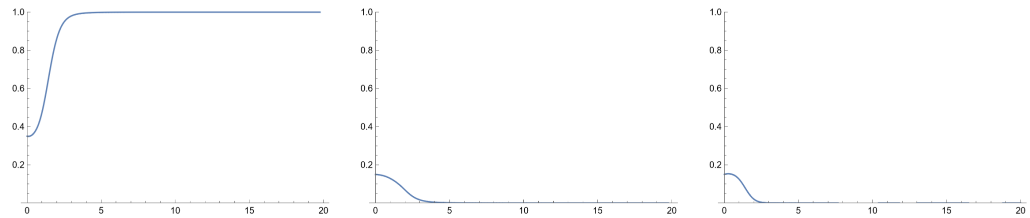
equations (PDEs), providing a powerful tool for mathematical analysis and simulation of complex dynamic systems.
NDSolve is highly flexible and can handle a wide range of differential problems, yielding numerical solutions that can be used for further analysis, simulations, or graphical visualizations. In cases such as ours, where coupled ODE systems are solved, NDSolve can return a list of ***InterpolatingFunction***([23]) objects corresponding to the different dependent variables.
In the following sections, the obtained results and the temporal trends of the different components analysed are shown.

5.1 Q-factors dynamics

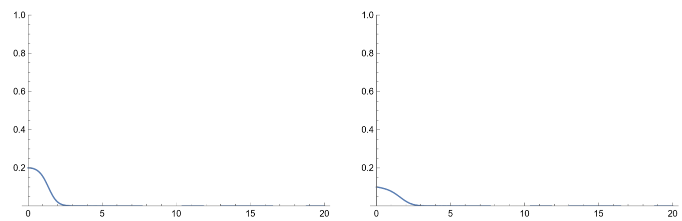
The first interesting result concerns the trend of the $x_{qi}(t)$ components, which, together with those of $z_{qi}(t)$, allows us to understand which Q-factor dominate all the others in the long term and, most importantly, whether the sign is positive or negative.
In figures 2 and 3, the trends of $x_{qi}(t)$ and $z_{qi}(t)$ for all five Q-factors are shown, respectively. The temporal evolution of these variables indicates that the "population" related to **Q-factor 1** is the one that grows and asserts itself over all the others, with the overall loading tending towards distinctly positive values. From this result, we can deduce that the population will likely stabilize according to the positive Q-factor 1 model, which, as we recall, was identified with the group of innovators defined as *Early Majority adopters*.
The evidence in [5] highlights that currently, *Early Majority adopters* are still in an initial stage of the evolution process, and the critical mass needed to trigger the persuasion process has not yet been reached. Our findings confirm that the diffusion process is in its initial phase but it is likely to evolve towards an increasing presence of such typology of adopters. Their *empirical experience* will be crucial in initiating imitation processes. However, it remains to be understood what the possible strategic evolution could emerge and which selective/diffusion models might come **in to the game**.

5.2 Strategy selection

The temporal evolution of $x_{qi}(t)$ and $z_{qi}(t)$ is connected to the evolution of the"populations" $y_i(t)$ related to the various strategies as defined in Table 1



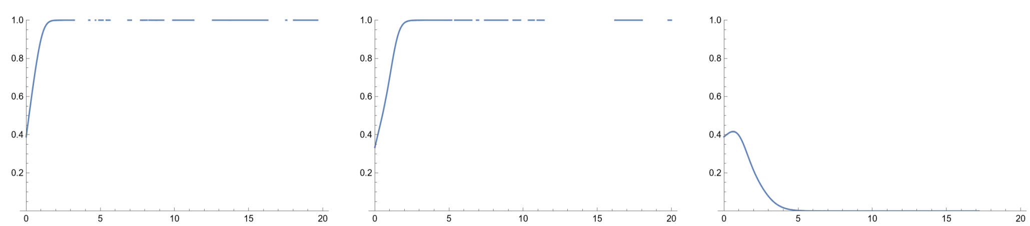
(a) Q-factor-1 (b) Q-factor-2 (c) Q-factor-3



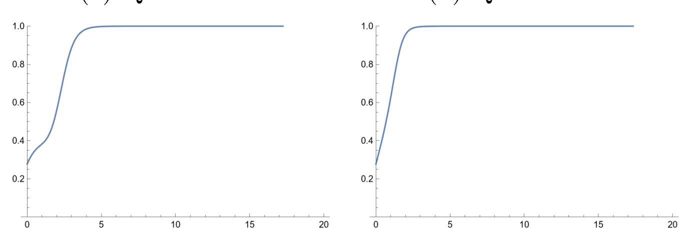
(d) Q-factor-4 (e) Q-factor-5

In the long run, the only surviving factor is Q-factor 1.

Figure 2: Trend of the five variables $x_{qi}(t)$ over time, the asymptotic value show that Q-factor-1 dominates over others.



(a) Q-factor-1 (b) Q-factor-2 (c) Q-factor-3



(d) Q-factor-4 (e) Q-factor-5

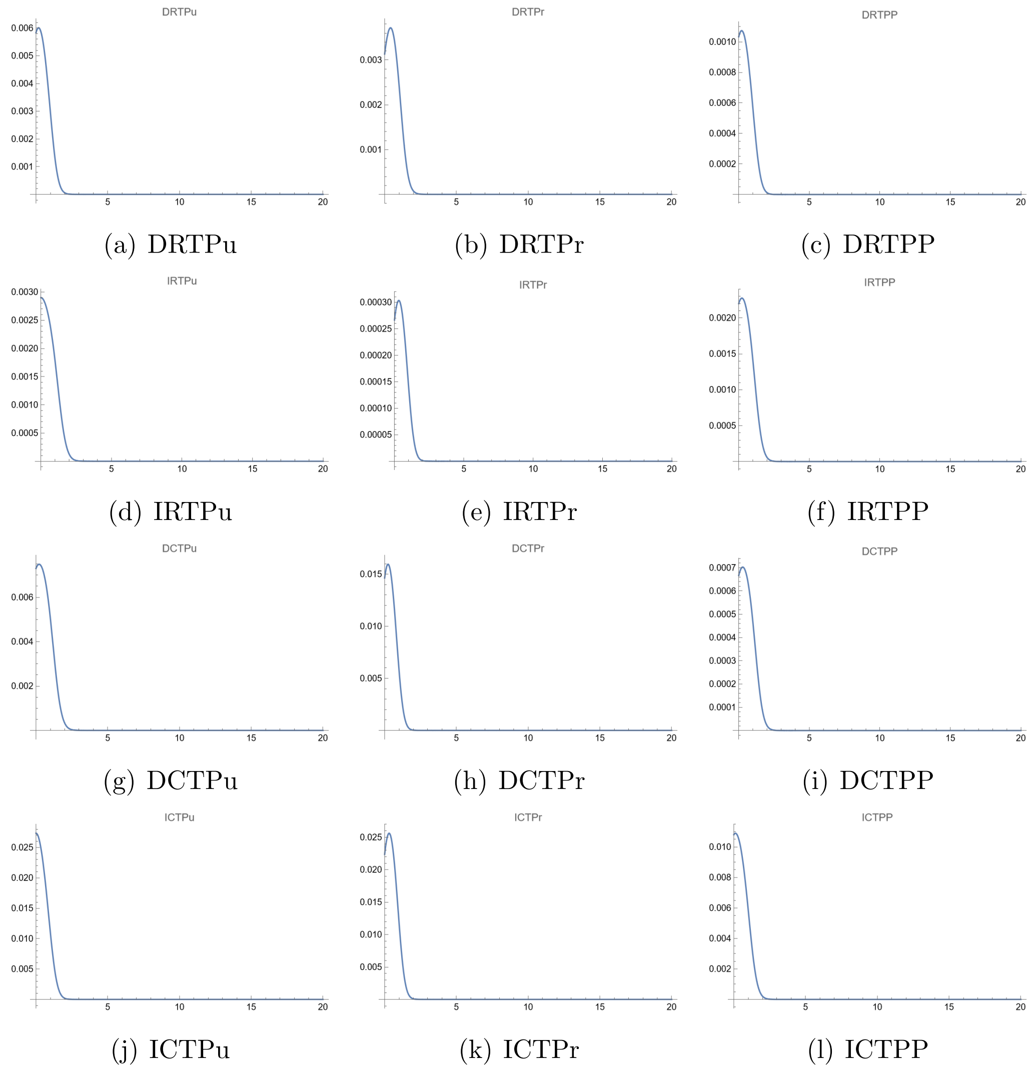
Please note that $z_{qi}(t) \overset{t\to\infty}{\longrightarrow} 1$ in case $+Q_i$ dominates $-Q_i$ and $z_{qi}(t) \overset{t\to\infty}{\longrightarrow} 0$ otherwise.

Figure 3: Trend of the five variables $z_{qi}(t)$ over time, the asymptotic value determines the main sign of the loading of the various Q-factors.
All Q-factors tend to positive values, except for Q-factor 3.

These populations clearly encompass not only the Tool dimension related to technologies, but also the other three dimensions analysed in the study (see Table 1). It is important to remember that the conditions imposed at $t = 0$ allowed each of the populations of the 36 strategies to be initially non-zero. This gives all of them the possibility to evolve (otherwise, if the initial population for any of the strategies had been zero, it would have remained zero and never "evolved"). The evolution of each of the 36 strategies is shown in Figures 4, 5, and 6. For a better understanding of the evolutionary dynamics, we have divided the 36 strategies into 3 groups based on the ***Tool*** component. Specifically, in Figure 4, the statements where the Tool variable takes the Traditional option are grouped; in Figure 5, those with the Standard option; and in Figure 6, those with the Advanced option.

Many populations fail to emerge, with values remaining very close to zero. Some populations initially tend to grow but subsequently decrease and tend to nullify over an average time. Only the population of strategy **DRAPP**, which started from an initial value lower than others (see Table 5), grows continuously and, with a typically sigmoidal trend, imposes itself over all the others.

These latest results depict an evolution of the system that goes through two successive selection phases. In the first phase, some strategies are immediately filtered out while others coexist, generating a mixed strategy that is a weighted combination of the initially surviving strategies (whose populations initially grow). In the subsequent selection phase, one strategy asserts itself over all the others. Lastly, it is also useful to investigate the temporal trend of the expected utility as the evolutionary process follows the different phases of selection. This trend is shown in Figure 7. It is interesting to note that the initial expected value, due to the initial mix of different variables, is negative; this value begins to grow initially at a rate that depends on the first phase of selection, where only some strategies are removed and the others are reshuffled into a better mix. Subsequently, the growth rate increases during the second phase of selection, where the system evolves towards a single final solution.



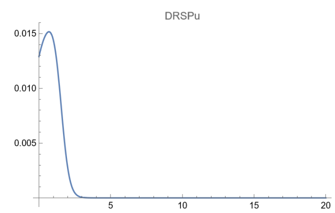
(a) DRTPu (b) DRTPr (c) DRTPP

(d) IRTPu (e) IRTPr (f) IRTPP

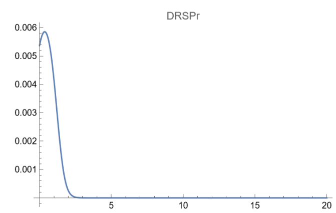
(g) DCTPu (h) DCTPr (i) DCTPP

(j) ICTPu (k) ICTPr (l) ICTPP

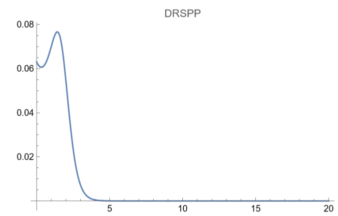
Figure 4: Trends of the variables $y_i(t)$ related to the strategies where the Tool dimension takes the Traditional $(\boldsymbol{T})$ option.



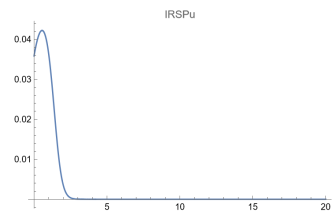
(a) DRSPu



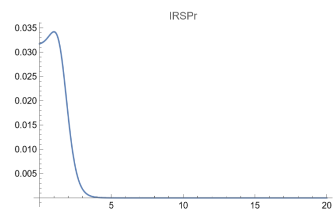
(b) DRSPr



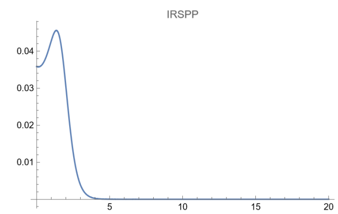
(c) DRSPP



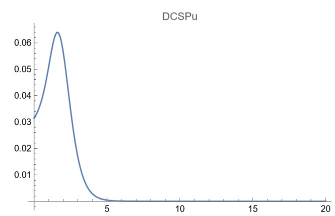
(d) IRSPu



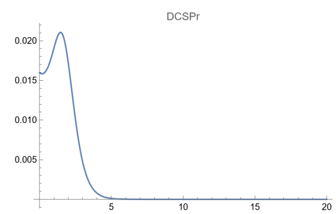
(e) IRSPr



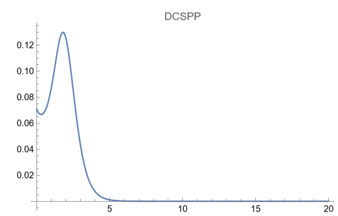
(f) IRSPP



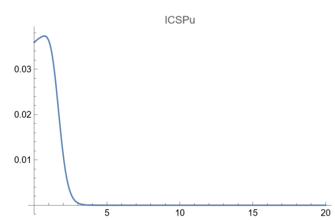
(g) DCSPu



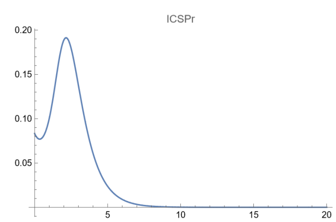
(h) DCSPr



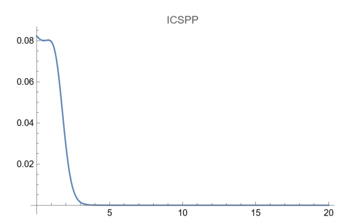
(i) DCSPP



(j) ICSPu

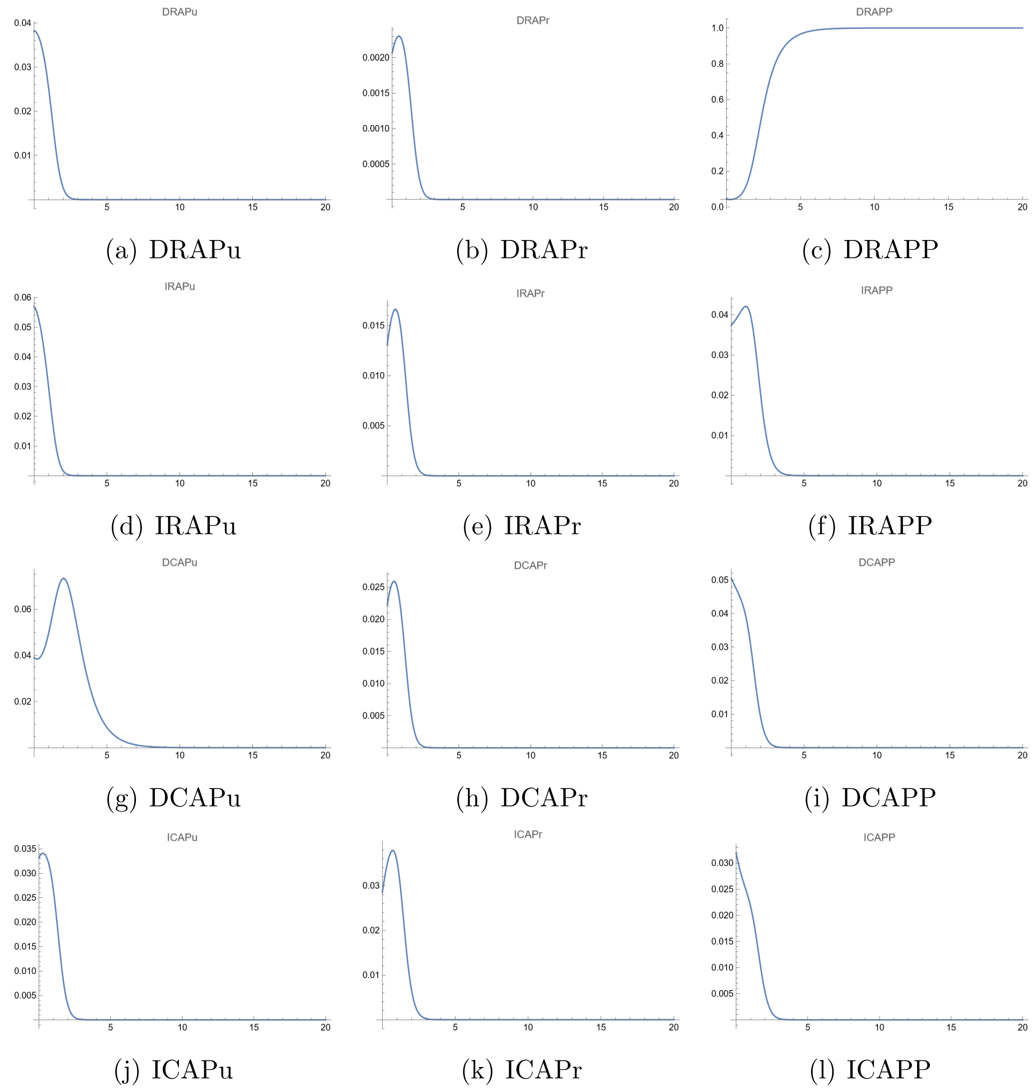


(k) ICSPr



(l) ICSPP

Figure 5: Trends of the variables $y_i(t)$ related to the strategies where the Tool dimension takes the Standard digital (S) option.



(a) DRAPu (b) DRAPr (c) DRAPP
(d) IRAPu (e) IRAPr (f) IRAPP
(g) DCAPu (h) DCAPr (i) DCAPP
(j) ICAPu (k) ICAPr (l) ICAPP

Figure 6: Trends of the variables $y_i(t)$ related to the strategies where the Tool dimension takes the Advanced digital ($\boldsymbol{A}$) option.

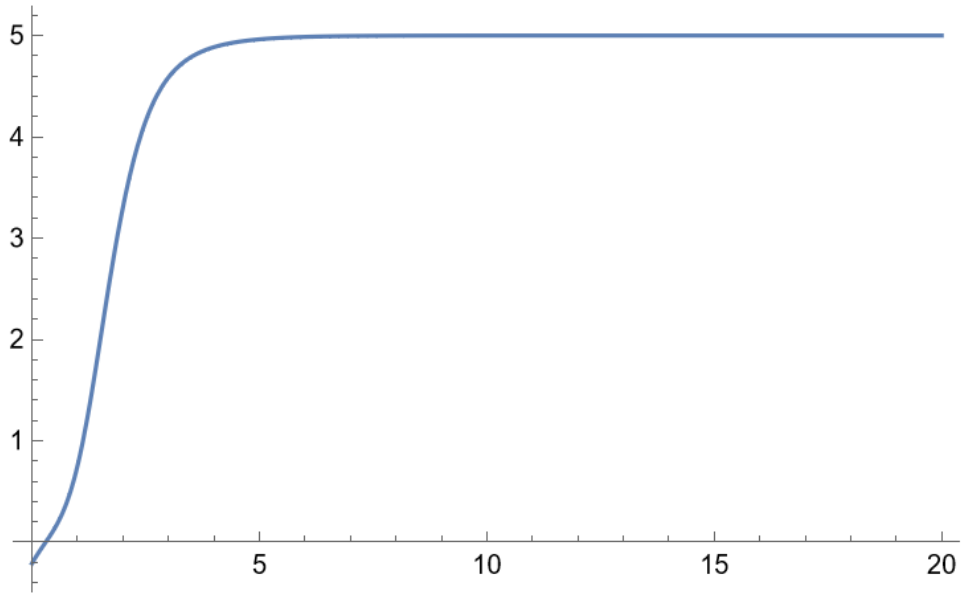


Figure 7: Expected total utility as function of t.

6 Conclusion

The integration of immersive technologies in cultural and tourism industries is at a critical juncture, driven by stakeholders' perceptions. These technologies promise to revolutionize experiences by offering unprecedented levels of engagement and interaction.By employing evolutionary game theory and Q-methodology, the competition between various strategies in a stakeholders perceptions point of view can be analyzed. In this paper, evolutionary game theory has been used to anticipate potential evolutionary paths within the economic system centred around cultural heritage and tourism, providing insights into how the ecosystem might evolve in adoption of immersive technologies based on evolutionary principles. The result of the evolution process thus leads to a selection among the initial mix of strategies, favouring the strategy that involves targeting local "consumers," with recreational content and the use of technologies such as the metaverse, AR (augmented reality), and VR (virtual reality), developed in co-participation between the public and private sectors. This strategy leverages cutting-edge technology to create immersive experiences that can significantly enhance the appeal and accessibility of cultural and tourist attractions. The potential success of these strategies lies in their ability to provide unique, interactive experiences that resonate with the local population. By focusing on recreational content, these initiatives make cultural heritage more accessible and enjoyable. Moreover, the collaboration between public and private sectors ensures a broad resource base, fostering innovation and sustainability. In the future, it would be beneficial to explore additional case studies to generate alternative evolutionary models and assess differences or similarities.

7 Acknowledgment

A pre-print version of this paper is available on arXiv:2409.06720 ([6])

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