Strategic Cooperation in the Metaverse: A Game Theory Analysis with Age Of Information

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***Abstract*—The Metaverse is an immersive online world, accessed through headsets, seamlessly integrating virtual and augmented reality. Users navigate this digital realm through avatars, participating in real-time activities such as work, meetings, concerts. The real-time nature of the Metaverse prompts an analysis using age of information, a metric that tracks information freshness. In this environment, where users actively seek continuous stimuli, sustaining high attention is vital. We propose a game-theoretic analysis of user-server interactions for enduring cooperation, where we incorporate a discount factor to quantitatively compare present and future actions. We derive closed-form solutions for the infinite horizon game and obtain lower bounds for the discount factor chosen by the entities and upper bounds for the communication cost sustainable in order to achieve long-lasting cooperation. This enriches our understanding of temporal dynamics in ensuring information freshness, providing insight into the dynamic interplay between users and the Metaverse environment.**

***Index Terms*—Game Theory, Metaverse, Age of Information, Dynamic Games, Discount factor.**

I. Introduction

The Metaverse is a new medium exploiting advanced technologies such as cloud computing, artificial intelligence (AI), as well as virtual and augmented Reality (VR/AR). It constitutes a new horizon for the interaction between virtual and natural worlds [1], [2]. The idea of MetaSocieties, existing alongside real societies, greatly expands living and working space for humans. The concept of digital twins is also based on providing descriptions, predictions, and prescriptions for the real counterparts through virtual and real interactions and closed-loop feedback [3].

Quality of experience (QoE) is an important concept to assess the participation of the users. In turn, it is influenced by multiple factors at the service layer, user layer, and environment layer, providing a direct reflection of the user's perception and recognition of the service. To optimize QoE, it is essential to tailor the design of the resource allocation scheme based on the diverse interests of users [4], [5].

The primary objective in the AR-VR design is to maximize user retention, which ultimately requires a characterization of human behavior. This is generally addressed through predictive models based on data analytics to anticipate user actions, allowing for more precise customization of the interactions [6]. One of such metrics is the attention focus index (AFI), defined as the quantification of the user attention, i.e. the level of the user interest for an object. User's eye movement is one of the key characteristics to reflect shifts in his attention. Alternatively, the head orientation is also an effective substitute of user's attention. Both eye movement and head orientation are sensed in real time by sensors integrated into the VR headset [7]. However, the issue of computational complexity emerges as the system involves multiple users and therefore a whole system characterization suffers from a dimensionality curse.

Modeling users interact in real time, presents a critical challenge related to managing information freshness [8]. We follow the most recent approaches in sensing networks and real-time applications, which quantify it through age of information (AoI) [9], defined as the period elapsed between the generation of data and its actual utilization. This reflects that the timeliness of updates is crucial to ensure a dynamic and accurate experience for the user [10], [11].

Quantifying real-time update mechanisms can provide a numerical assessment of the Metaverse's efficiency. This guarantees that the virtual environment consistently reflects the most recent information, ensuring temporal relevance of data and ultimately improving the user's experience [12].

The primary objective of communication exchanges is to ensure timely transmission and maintenance of information within the virtual environment. To evaluate this objective, we employ an extension of AoI known as discounted age of information (DAoI) [13], and extend its role to the cooperative dynamics between separate entities. Specifically, we assess the establishment and maintenance of cooperation by examining various values of the discount factor through a game theoretical analysis [14]–[17].

We derive closed form expressions for the discount factor that agents have to apply to achieve long-lasting cooperation as a function of the transmission probability and cost. We argue that high discount factors are needed to foster collaboration at regimes with high transmission rates when communication is costly [18], [19]. We further derive upper bounds for sustainable transmission costs as a function of the transmission probability and the discount factor.

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The remainder of this paper is structured as follows. Sec. II examines the existing literature on the Metaverse applications and the role of freshness of information in these scenarios. Sec. III outlines the scenario of the interactive Metaverse application. Sec. IV models the previously defined scenario as a multistage game and derives the expressions of the conditions for long-term collaboration. Sec. V discusses the numerical results and finally Sec. VI draws the conclusions.

II. Related Work

The rise of the Metaverse is expected to impact on the way we conduct business, interact with brands and others, and develop shared experiences. The line between physical and digital will be more and more faded and many challenges related to governance and ethics will arise [2].

Therefore, the Metaverse has brought forth a multitude of studies covering diverse areas of knowledge. Notable examples include new educational methodologies [20], which have the potential of exploiting the Metaverse to promote inclusion, especially in cases of motion impairments or other physical disabilities. Enterprises and societies are closely monitoring the development of a completely new virtual world, with a keen interest in opening MetaEnterprises and MetaCities [3].

However, growing involvement of digital twins in these areas raises significant privacy and security concerns. Recent studies [1], [21] delve into critical challenges in security defenses and privacy preservation within the distributed Metaverse architecture. Additionally, potential solutions involving the design of security and privacy countermeasures are also explored. This can also lead to game theoretic approaches, where the strategic roles of network users and adversaries are explored [14], [22].

The Metaverse also entails real-time interactions, translating into stringent requirements for a fully immersive experience, large-scale concurrent users, and seamless connectivity. Challenges associated with the sixth generation (6G) wireless system are discussed in [23].

Due to the importance of exchanging up-to-date information among digital twins, it would seem natural to consider AoI in related evaluations, as argued in [10]. However, we notice that AoI is rarely addressed by papers dealing with multimedia applications in the Metaverse. AoI was introduced in seminal works such as [9] to extend concepts of information freshness/staleness [8] and finds natural applications in scenarios with process monitoring in real time, as is the case for vehicular networks [24], [25].

This may be the case for several different scenarios in the internet of things (IoT), which are envisioned to support many aspects of our daily lives, requiring real-time monitoring and tracking. However, data exchanges among Metaverse devices involve various tradeoffs, for example between reliability and timeliness. Retransmission-based error control techniques need to be adaptively managed depending on network conditions and application requirements, possibly leveraging incremental redundancy and correlation [26], [27].

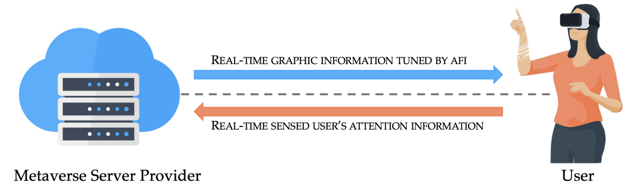

Fig. 1. Graphical representation of the scenario between the MSP and the user. The user sends to the MSP its attention information and the server provides the user with personalized graphical rendering based on user's data

A limitation against frequent updates is the energy consumption of wireless devices that are not powered through cables. The updates have to be managed, and the power expenditure of different policies must be taken into account in order to choose the best solution for every situation [19], [28]. For scenarios involving the Metaverse and digital twins, personalized devices are willing to receive loads of information for better context awareness, yet they may be shy to share their data to save energy.

This can lead to a game theoretic approach for AoI in the Metaverse, where we observe how the Nash equilibrium (NE) of a game can change if the objective is to minimize a sum of AoI and a cost [17]. In this context, Metaverse agents act selfishly, i.e., driven by their own interests, their ideal scenario being to be fed with plenty of data by other agents without necessarily contributing and draining their communication resources. However, the emergence of collaboration, as common in network scenario, is necessary to establish a satisfactory QoE [15], [16].

III. System Model

We consider a scenario where a Metaverse server provider (MSP) and an immersed are exchanging information. The MSP is responsible for delivering details about the virtual world, while the user is sharing his/her attention focus index (AFI) data. This exchange of information is advantageous for both parties involved: leveraging user-provided data, the MSP can deliver the virtual world's appropriate perspective to the user, with each element rendered at an optimal level of detail based on the user's AFI. This approach prevents the unnecessary allocation of resources by tailoring information to what the user is currently viewing [11]. Simultaneously, the user seeks immersive engagement in the Metaverse, and gameplay fluidity is a critical parameter for assessing the QoE. Furthermore, the MSP is motivated to collect user data for self-improvement through the creation of a dataset for learning to predict users' attention transactions. A high-level graphical description of this scenario can be seen in Fig. 1. Since in a real-time application, information freshness is essential, and similarly in our scenario, it is crucial that the user's view is consistently updated and remains coherent, the AoI is a suitable metric to assess the entities' performance throughout the interaction [29]. By defining the entity's transmission probability p and the reliability of the information channel P_{succ}, the probability of performing correctly an information update is $\rho = P_{\text{succ}}p$ Therefore, the expected AoI for entity i $\mathbb{E}[\delta_i]$ can be computed as [17]

$$\mathbb{E}[\delta_i] = \frac{1}{\rho} - 1\,. \tag{1}$$

A high update rate appears to be a good choice for low AoI, yet we want to also include that each transmission incurs a cost. To this end, we assume a price c paid by the entity that attempts to transmit. This factor accounts for both the energetic resource consumption and confidentiality concerns, as private data are shared by users [18], [30].

We evaluate this information exchange over an infinite horizon to investigate the establishment of cooperation between the two entities. Thus, we include a discount factor $\theta \in [0, 1]$ in the utility received by the MSP and the user in future interactions. This leads us to adopt discounted age of information (DAoI) $\mathcal{D}_\theta$ as defined in [13], i.e.,

$$\mathcal{D}_\theta = \frac{\sum_{k=0}^{\infty}\left(\sum_{j=0}^{k} j\theta^j\right)\rho(1-\rho)^k}{\sum_{k=0}^{\infty}\left(\sum_{j=0}^{k} \theta^j\right)\rho(1-\rho)^k} \tag{2}$$

which in our case can be reduced to

$$\mathcal{D}_\theta = \frac{\theta\rho(1-\theta+\theta\rho)}{(1-\theta)^2}\left(\frac{1}{\rho} - \frac{1-\theta+\theta\rho+\theta(1+\theta)(1-\rho)}{(1-\theta+\theta\rho)^2}\right)\,. \tag{3}$$

IV. Game Theoretic Analysis

The scenario described in the previous Section is modeled as a *multistage game* which is a finite sequence of normal-form stage games. Each stage game is an independent, well-defined game of complete but imperfect information (a simultaneous-move game). These are played sequentially by the same players, and the total payoffs for the sequence of games are evaluated using the sequence of partial outcomes [15]. After each stage is completed, all the players observe the outcome of that stage, and this information structure is common knowledge.

The players of our multistage game are the user and the MSP. In each stage, they both can choose between two actions: *Collaborate* (C) or *Defect* (D). Playing C involves performing an information update with probability ρ, whereas playing D is equivalent to deciding not to transmit. We assume that the players choose simultaneously in each round of the game and that the game is symmetric, meaning that probabilities and costs are equal for both players.

We define the utility rewarded to the player that plays C for a one-shot interaction, that is transmit an update, as

$$u_j^C = -\mathbb{E}[\delta_j] - cp = -\frac{1}{\rho} + 1 - cp\,. \tag{4}$$

Similarly, the utility for playing D is

$$u_j^D = -\mathbb{E}[\delta_j] = -\frac{1}{\rho} + 1\,. \tag{5}$$

TABLE 1
STAGE GAME: ROWS REPRESENT THE ACTIONS SELECTABLE BY THE USER, WHILE COLUMNS REPRESENT THE ONES AVAILABLE TO MSP

	C	D
C	$-\frac{1}{\rho}+1-cp$, $-\frac{1}{\rho}+1-cp$	$-\frac{1}{\rho}+1-cp$, $-\frac{1}{\rho}+1$
D	$-\frac{1}{\rho}+1$, $-\frac{1}{\rho}+1-cp$	$-\frac{1}{\rho}+1$, $-\frac{1}{\rho}+1$

Note the minus sign for the expected AoI and the transmission cost as they both have to be minimized.

In the scenario where both players choose C, if we consider an ideal transmission channel and $\rho \to 1$, we get $\delta \to 0$. In this case, the utilities are influenced solely by the transmission costs. If both players choose D, both experience an increase in AoI, but they do not incur any cost. If one player plays C and the other plays D, the latter benefits from the cooperation of the other and does not bear the transmission cost. Conversely, the player who played C pays the transmission cost and ends up with higher AoI. The utilities of the two players in the stage game are presented in Tab. 1. We can observe, therefore, that the best response for both players is to choose *Defect*. Similarly to the Forwarder's dilemma [31], the problem presents a unique Nash equilibrium coinciding with the best response of the two players and does not involve mixed Nash equilibria [16]. In a finite-horizon multistage game consisting of T stage-games played in each of the periods $1, 2, \ldots, T$. Let u_i^t be player i's payoff from the anticipated outcome in the stage-game played in period t. We denote by u_i the present-time total payoff obtained by i from playing a certain sequence of moves, defined as

$$u_i = u_i^1 + \theta u_i^2 + \theta^2 u_i^3 + \ldots + \theta^{T-1}u_i^T = \sum_{t=1}^{T}\theta^{t-1}u_i^t\,, \tag{6}$$

i.e., the discounted sum of payoffs that the player expects to get. For the assessment of the multistage game with an infinite horizon, we introduce a *grim trigger* strategy to enforce cooperation between players. The grim trigger assumes that each player initially cooperates and continues playing this way as long as all the interacting players also cooperate [15]. However, if a defection (failure to cooperate) happens at any point in time, the player implementing the grim trigger strategy responds by defecting for the remainder of the game. This is a form of punishment for defection, and aims to sustain cooperation in repeated interactions. The key idea is that players are deterred from deviating from cooperation because the consequences of defection are severe and long-lasting. If two interacting players play a grim trigger strategy, they initially cooperate and receive the benefits of mutual cooperation, which creates a positive outcome for both, and the grim trigger maintains cooperation for future interactions. Thus, in game theoretic terms, this represents a subgame perfect equilibrium, if and only if a single deviation, bearing ever lasting consequences, does not provide a better present-time advantage, which is computed through discounting future utilities as in (6).

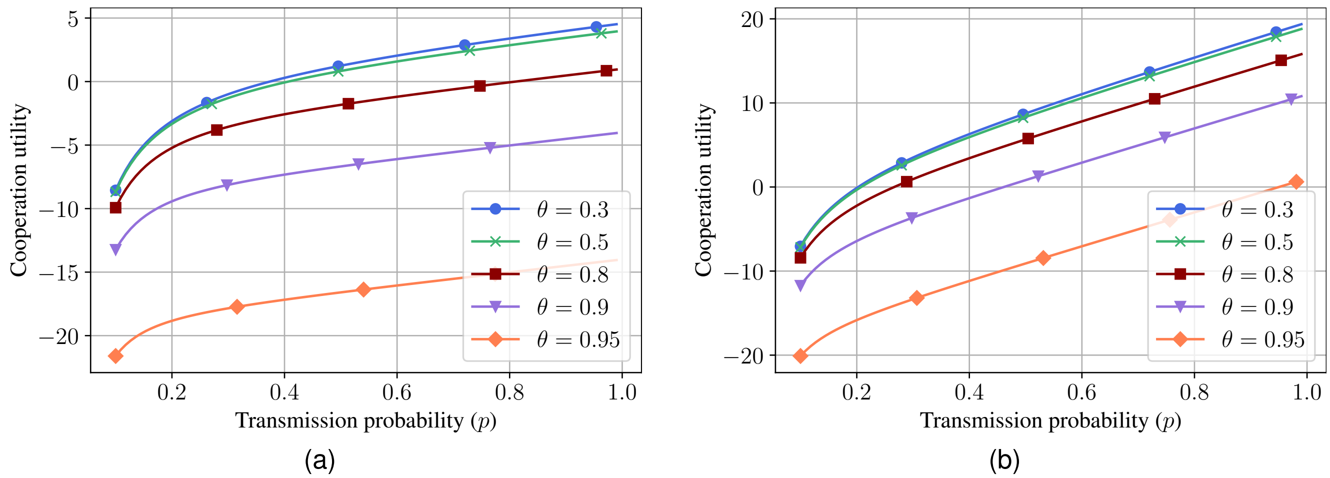

Fig. 2. The grim-trigger strategy, dependent on p, with two different fixed costs. (a) $c = 5$, (b) $c = 20$

In the multistage analysis, we consider DAoI as the main component of the utility for the users. As argued in [13], the standard quantization of AoI diverges for $\rho \to 0$, whereas DAoI is bounded, allowing us to consider infinite iterations and evaluate ρ values close to zero. It can be noted that with $\theta \to 0$, these two metrics correspond, and in the assessment of the discounted infinite game, the DAoI proves to be consistent.

To establish and maintain cooperation, it must be more advantageous than the possibility of deviating from cooperation by playing *Defect*. If ρ tends to zero, corresponding to playing (D, D) at each stage indefinitely, the DAoI becomes

$$\mathcal{D}_{\theta_{\rho \to 0^+}} = \frac{\theta}{1-\theta}. \tag{7}$$

Therefore, under the hypothesis of a perfect communication channel ($\rho = p$), the following inequality must be satisfied

$$-\frac{1}{p} + 1 - \frac{\theta}{1-\theta} \leq -\mathcal{D}_\theta - cp. \tag{8}$$

The first term of the inequality represents the scenario in which a player decides to play D in the first round to avoid incurring the cost associated with playing their best response in the stage game but subsequently faces punishment in all subsequent iterations that is the forever defect of the other player. The second term depicts the scenario in which collaboration is established in the first round and maintained throughout the game.

The goal is to identify the values of the discount factor that ensure cooperation over time, so we have to isolate θ from (8), and after some algebra:

$$\theta \geq \frac{\frac{c\,p^3}{2} - c\,p^2 + p\,\frac{\sqrt{c^2\,p^4 + 2\,c\,p^2 + 4\,p - 3}}{2} - \frac{3\,p}{2} + 1}{c\,p^3 - c\,p^2 - 2\,p + 1}. \tag{9}$$

To deepen the dependency of the cost from the transmission probability we have also computed the threshold value of the cost as a function of p and θ, that is:

$$c = \frac{\theta^2\,p^2 - 2\,\theta^2\,p + \theta^2 + 3\,\theta\,p - 2\,\theta - p + 1}{p^2\left(-\theta^2\,p + \theta^2 + \theta\,p - 2\,\theta + 1\right)}. \tag{10}$$

V. Results

We present a series of visual assessments designed to underscore the key findings of the previously discussed analysis. First of all, we have to clarify that the transmission probability p is independent from player choices: they can decide whether to transmit with a certain transmission probability or to not transmit at all. Central to our investigation is the examination of the influence of the discount factor θ as it can be tuned to devalue the future over the present. The focus is on the grim trigger inequality (8), examining when the inequality is satisfied, i.e., when the curves of the collaboration utility go below zero. Fig. 2 illustrates how a higher value of θ allows the selection of higher transmission probabilities, while with a lower θ, the curves intersect the x-axis with progressively lower values of p. This behavior is significantly influenced by the cost. In Fig. 2b, we have quadrupled the cost value to observe how the transmission probability changes. We observe that the function is monotonically increasing, so it does not have points of maximum and minimum. This emphasizes the importance of tuning θ and p, since there is not a globally-optimal working point for the system. The inequality is satisfied when the curves for the cooperation utility go below zero, so we need to choose the appropriate threshold value in order to maximize the utilities of our players depending on the current transmission probability.

It has to be noted that a higher transmission probability implies an increase in cost paid by the entities. Consequently, even with a high value of θ, as the cost increases, the transmission probability satisfying the inequality begins to decrease. We can also observe that there is a significant gap between curves corresponding to values for the discount factor that are very close (e.g., $\theta = 0.9/0.95$), while the gap is

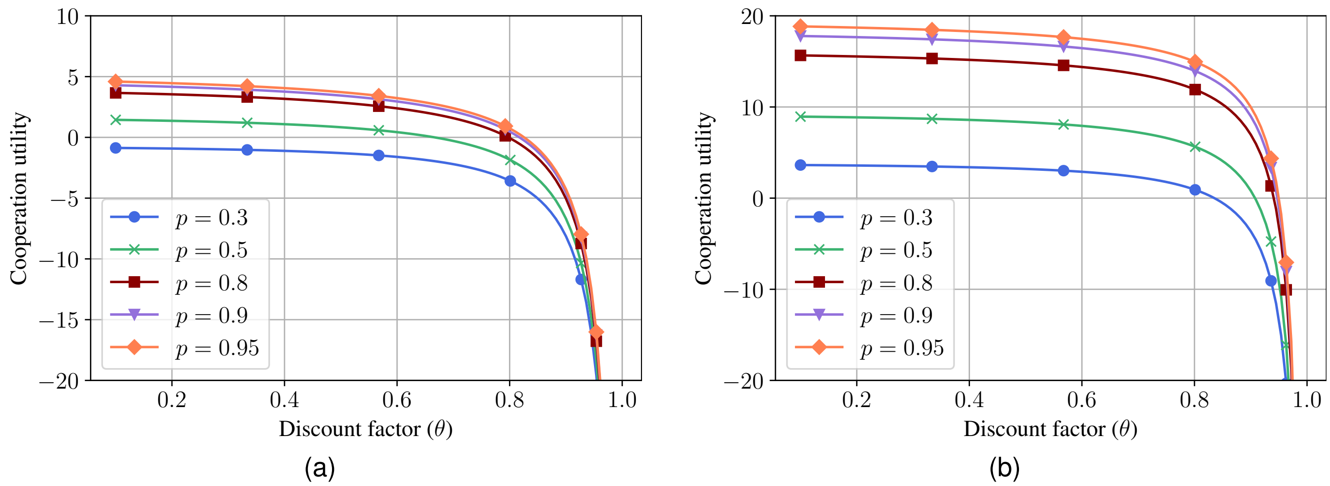

Fig. 3. The grim-trigger strategy, dependent on θ, with two different fixed costs. (a) $c = 5$, (b) $c = 20$

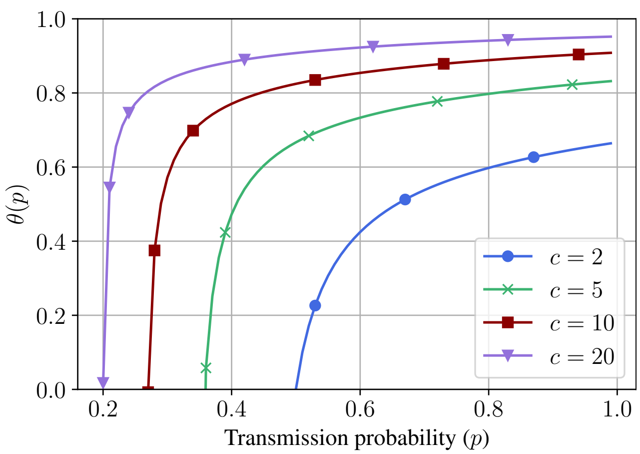

Fig. 4. θ threshold function, as a function of p

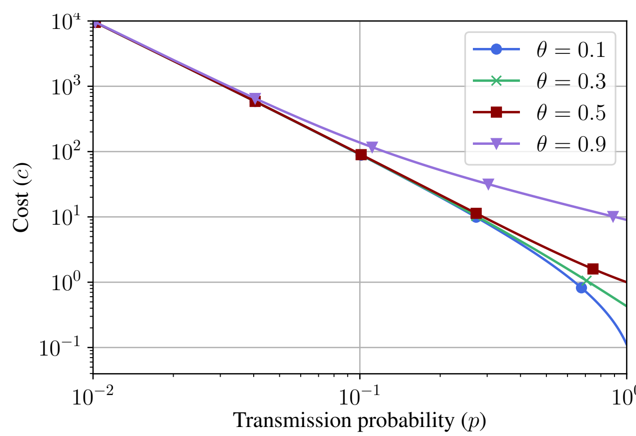

Fig. 5. Cost threshold function, as a function of p

smaller between 0.3 and 0.5; this indicates that variations around small values of θ have limited impact, but the system becomes highly sensitive to variations in θ when the value is close to 1.

In Fig. 3, we set different values for p and vary the discount factor. As previously stated, the solution for the inequality is when the collaboration utility goes below zero. With $p = 0.8$, the curves intersect the x-axis at $\theta = 0.8$, whereas, with a higher cost, the same curve crosses the threshold at $\theta = 0.94$. This indicates the need for a higher discount factor to enable players to transmit with high probabilities; otherwise, the high cost will lead to mutual Defect.

Fig. 4 illustrates the relationship between θ and p, providing a visual representation of (9) under equality sign. This means that $\theta(p)$ is the minimal discount factor that allows collaboration given the transmission probability. As expected, growing cost values lead to increasing discount factors for the same transmission probability. Interestingly, for the considered cost values, it is always possible to tune the discount factor in order to achieve infinite-horizon collaboration between the players.

Fig. 5 displays the solution of (10) as a function of p. By setting a specific value for θ, we gain insight into the maximum cost that can be imposed to foster collaboration, depending on the given value of p. It should be noted that only values of θ close to 1 allow long-lasting collaboration to emerge. Conversely, small discount factors are more prone to inducing anti-collaborative behavior of the players. This is especially true when $c \approx p$ as in this case, the cost of transmission should be aided by an incentive given to the player to communicate as in these scenarios communication is considered very hard to establish.

VI. Conclusions

We analyzed cooperation dynamics between users in the Metaverse through a quantitative investigation [15]. We conducted a game-theoretic analysis, modeling the scenario as a multi-stage game with infinite horizon, introducing a discount factor, and a Grim Trigger strategy. We used discounted AoI and assessed for which discount factor cooperation is sustained, an important aspect for the users' QoE.

We observed that a higher discount factor is always preferable to ensure and sustain long-term cooperation as it is more robust to higher costs associated with the transmission. We have also derived the minimal threshold for the discount factor for which we can guarantee collaboration between the players, based on the transmission probability p and the cost factor c. We have also derived an upper bound for the cost factor that allows long-term collaboration to emerge with the threat of a grim trigger strategy. We also argued that for low discount factor values and high transmission probability collaboration between the players can only emerge when an incentive mechanism is in place to encourage transmission.

Future studies more targeted towards data collection could be instrumental in expanding our analysis to gain a richer understanding of cooperative dynamics and optimize user experiences within virtual environments, for instance considering digital twins to simulate interactions in the digital world.

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