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An evolutionary game theoretic perspective on e-collaboration: The collaboration effort and media relativeness

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Abstract

Studies of e-collaboration from a game-theoretical perspective are practically nonexistent. This article contributes to filling this gap by focusing on the strategic interaction between players as they decide whether and how much to collaborate with each other. We use evolutionary game theory to make predictions about a two-person e-collaboration game. More specifically, we extend the traditional Prisoners' Dilemma and Snowdrift game theory notions to discrete-strategy e-collaboration games, by explicitly including social punishments into the players' payoff functions. We also introduce continuous-strategy e-collaboration games with both complete and incomplete information. Finally, we provide two generic dynamic programming models for e-collaboration games with media selection.

Keywords: e-Collaboration; Collaboration effort; Media selection; Evolutionary game theory; Social punishment

1. Introduction

e-Collaboration is generally defined as collaboration among different individuals to accomplish a common task using electronic technologies (Kock, 2005b). In recent years, e-collaboration has emerged as a new research area especially thanks to the popularity of Internet, e-mail, and other modern electronic technologies. The e-collaboration research literature has addressed several key topics on collaboration media (Daft and Lengel, 1986; Daft et al., 1987; Kahai and Cooper, 2003; Kock, 2001), collaboration behavior (Kock, 2001; Kock, 2004), and electronic technologies (Lee, 1994; Markus, 1992; Markus, 1994; Markus, 2005).

According to Myerson (1997), "a game refers to any social situation involving two or more individuals." Naturally, an e-collaboration task can be modeled as a cooperation game. However, to the best of our knowledge no studies have looked at e-collaboration from a game-theoretical perspective. On the other hand, cooperation game theory has been widely applied in biological and sociological investigations (Axelrod and Hamilton, 1981; Axelrod, 1984; Axelrod and Dion, 1988; Doebeli et al., 2004). However, these studies generally utilize the theories of Prisoners' Dilemma (PD) and Snowdrift Dilemma (SD) Games to study the evolutionary stability of a sizable population (Doebeli and Hauert, 2005). While e-collaboration among industrial partners and individual researchers becomes more and more popular (Griffith et al., 2003; Powell et al., 2004; Sole and Demonson, 2002; Townsend et al., 1998), it would be useful to provide a theoretical guidance for the strategic interaction in a small-group e-collaboration game.

In this article, we study an e-collaboration game between two collaborating parties, e.g., co-workers or researchers. Two-person e-collaboration teams are very visible in academia and industry. Due to different working backgrounds, hardware availability, business agendas, and many other factors, collaborators could face dilemmas on whether to contribute more to the e-collaboration task or not. On choosing media during the e-collaboration, collaborators

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could face another problem that which medium is more effective if the collaborators have different preference over alternative media. In this article, we start from a symmetric discrete-strategy e-collaboration and then provide a discussion on a continuous-strategy e-collaboration game with incomplete information. Furthermore, we discuss a dynamic media selection game in both discrete-strategy and continuous-strategy settings.

The rest of this article is organized as follows. In the following section, we provide an introduction to the evolutionary game theory and the model. In Section 3, we present three different e-collaboration games and show properties related with these games. Section 4 analyzes a media selection game and discusses the media relativeness theory. We conclude in Section 5.

2. Background of the evolutionary game and the model

Evolutionary game theory, arising as an application of game theory to biological evolution contexts, has been utilized in other social areas, e.g., economics and business. According to Stanford Encyclopedia of Philosophy,[1] "evolution" does not need to be biological evolution and "changes in beliefs and norms over time." The first approach of evolutionary game theory can be traced back to Smith et al. (1973), in which the concept of the Prisoner's Dilemma game is employed. Axelrod and Hamilton (1981), Axelrod and Dion (1988) further use the iterated Prisoner's Dilemma to model the evolution of cooperation in studying the biological population dynamics.

Table 1 shows a Prisoner Dilemma (PD) game. We have two players, Player 1 and Player 2. Both players have two optional strategies, either to cooperate or to defect. In the table, $\{R, R'\}$, $\{S, T'\}$, $\{T, S'\}$ and $\{P, P'\}$ are the payoff vectors in the game. In this two-player game, T, R, P, and S denote the payoffs of Player 1 in different information states, and T', R', P', and S' denote the payoffs of Player 2. Throughout this article, we let the first item in a payoff vector be the payoff of Player 1 and the second item be the payoff of Player 2 as shown in Table 1. For example, $\{R, R'\}$ denote the payoffs of Player 1 and Player 2 respectively when both players decide to cooperate. In a PD game, $T > R > P > S$ and $T' > R' > P' > S'$. When $T = T'$, $R = R'$, $P = P'$, $S = S'$, the PD game is symmetric. Tit-for-Tat, in which a player will do whatever the other did on the previous move, is an optimal strategy for PD games (Axelrod and Hamilton, 1981; Axelrod, 1984). However, {Defect, Defect} is the only evolutionarily stable solution (Hauert and Doebeli, 2004), because to defect is the dominant strategy for a player no matter whether the other player chooses to cooperate or to defect. {Defect, Defect} is also the unique *Nash equilibrium*, which is defined as a status in which no player can be better off by deviating from the original strategy unilaterally.

[1] http://plato.stanford.edu/entries/game-evolutionary/.

Table 1
The Prisoner's Dilemma game

Player 1	Player 2	
	Cooperate	Defect
Cooperate	R, R'	S, T'
Defect	T, S'	P, P'

The property of the evolutionarily stable, non-cooperative state in PD games might conflict the common sense of some successful e-collaboration cases in Snowdrift (SD) game (or Hawk–Dove game or Chicken game), another famous cooperative game. A SD game describes such a situation that two drivers are trapped on a side of a snowdrift. Each driver has the option to start shoveling or stay inside the car. The game can be expressed by the same matrix as shown in Table 1, except that the constraints for SD games become $T > R > S > P$ and $T' > R' > S' > P'$. "The fundamental difference between the PD and SD is that in the SD, cooperation is the better option than defection when the opponent defects," according to Doebeli and Hauert (2005).

The Nash equilibria of $\{\text{cooperate}, \text{defect}\}$ or $\{\text{defect}, \text{cooperate}\}$ in SD games might well explain the evolutionarily stable proportion of cooperators in the biological world. However, the dynamic interaction between players, e.g., under what conditions the e-collaboration partners are willing to cooperate, is not well documented. According to the Stanford Encyclopedia of Philosophy, "most of the evolutionary game-theoretical models developed to date have provided the crudest approximations of the real cultural dynamics driving the social phenomenon in question." Few have described models of real e-collaboration games. Moreover, the domain of human cooperation might exceed the scope of PD and SD games for a large biological population.

In this article, we focus on a two-person e-collaboration game, e.g., an e-collaboration between two distant collaborators. We consider several scenarios: (1) a discrete-strategy game in which players have two options although they can play mixed strategies; (2) a continuous-strategy game in which players play continuously anywhere between cooperation and defection; (3) a media selection game as a part of a dynamic e-collaboration game.

To study the discrete-strategy game for two players, we start with the intuitive symmetric SD model as shown in Table 2. The left items are the payoffs of Player 1, for example, in $\{b, b-c\}$. b is Player 1's payoff, and $b-c$ is Player 2's payoff, where c is the cost to Player 2 given

Table 2
The Snowdrift game

Player 1	Player 2	
	Cooperate	Defect
Cooperate	$b-c/2$, $b-c/2$	$b-c$, b
Defect	b, $b-c$	0, 0

Table 3
The players' effort matrix

Player 1	Player 2	
	Cooperate	Defect
Cooperate	p, q	p, $1-q$
Defect	$1-p$, q	$1-p$, $1-q$

that Player 2 cooperates while Player 1 defects. When both players cooperate, the cost to each player is reduced to $c/2$. If both players defect, the payoff is zero for both players. For the players, a pure strategy is either to cooperate or to defect. A mixed strategy is a probabilistic combination of two strategies in which a player might play one strategy with a probability p and play another strategy with a probability $1-p$. For a SD game, a mixed strategy can be understood as an individual's propensity or willingness to cooperate (Hauert and Doebeli, 2004; McElreath, 2003). The literature tends to consider mixed strategy as an inferior but optional choice when the pure strategy cannot be found. In fact, as we may observe, it is common for participants, humans, to partially contribute their resources, e.g., energy, time, money, etc., in an e-collaboration game even if they decide to cooperate. We may use a continuous-strategy game to model a general e-collaboration game. However, for a discrete-strategy game, we argue that the mixed strategies might be considered as a continuous effort that a player is willing to contribute to the e-collaboration. Thus, we can consider a mixed strategy essentially as an effort matrix (see Table 3). If the participant decides to defect, the effort equals zero. If the participant decides to completely cooperate, this implies that the participant will try her/his best to cooperate with her/his full energy, time and other resources. This concept holds for a continuous-strategy game in which we can incorporate the collaboration effort into a closed-form utility function rather than a matrix. In the continuous-strategy game, we also discuss the impact of information on players' e-collaboration behaviors. Both the discrete-strategy game and the continuous-strategy game focus on the interaction between players to decide whether to collaborate and how much to contribute to the collaboration.

While there have been many discussions on the influence of media on e-collaboration effectiveness, this article provides an evolutionary game-theoretical perspective on the media selection.

3. The strategic interaction and the collaboration effort in e-collaboration games

We first start from a generic e-collaboration game without consideration of the media selection. In contrast to other investigations, we focus here on two main elements: (a) the dynamics of strategic interaction between players, and (b) the effort the players contribute to the e-collaboration.

3.1. A discrete-strategy e-collaboration game with social punishment

We continue from the previous symmetric SD model as shown in Table 2. However, we introduce an adjustment factor into the SD game. As shown by Axelrod and Dion (1988), Brandt et al. (2003), Doebeli and Hauert (2005), Fehr and Gachter (2002), Fehr and Fischbacher (2003), Jaffe (2004), McElreath (2003), Milinski et al. (2002), reputation, punishment, shadow of future, altruism and other psychological and sociologic factors play roles in individual behaviors in a cooperation game. In this article, we are not going to specify on each of these factors but conglomerate them into a single factor called *social punishment*, which is denoted by δ. In this e-collaboration game, we assume that a player will be punished, e.g., his/her reputation gets hurt, etc., if he/she decides to defect while the other cooperates. As a result, the defector's payoff decreases due to the impact of δ. We model a symmetric e-collaboration as shown in Table 4. Thus, Player 1's expected payoff is given by

$$\Pi_1(p) = pq(b-c/2) + p(1-q)(b-c) + (1-p)q(b-\delta), \quad (1)$$

$$\Pi_2(q) = pq(b-c/2) + q(1-p)(b-c) + p(1-q)(b-\delta). \quad (2)$$

Taking the first-order differential on $\Pi_1(p)$ with respect to p results in

$$\frac{\partial \Pi_1(p)}{\partial p} = q(b-c/2) + (1-q)(b-c) - q(b-\delta)$$
$$= b - c - q(b - c/2 - \delta). \quad (3)$$

Let $\frac{\partial \Pi_1(p)}{\partial p} = 0$ and we obtain the optimal solution:

$$q^* = \frac{b-c}{b-c/2-\delta}. \quad (4)$$

Since the above equation is independent of p, similarly and symmetrically, we have

$$p^* = \frac{b-c}{b-c/2-\delta}. \quad (5)$$

Given that $b - c/2 - \delta \neq 0$, from Eqs. (3)–(5), we obtain the following properties.

Proposition 1. *Consider a two-player symmetric e-collaboration game as shown in Table 4,*

(1) $\{p^*, q^*\}$ *is a symmetric Nash equilibrium as long as* $0 \leqslant \frac{b-c}{b-c/2-\delta} \leqslant 1$, *which is equivalent to* $b \geqslant c \geqslant 2\delta$ *or* $b \leqslant c \leqslant 2\delta$, *where* $\{p^*, q^*\}$ *are given by (4) and (5).*

Table 4
A symmetric e-collaboration game

Player 1	Player 2	
	Cooperate	Defect
Cooperate	$b-c/2$, $b-c/2$	$b-c$, $b-\delta$
Defect	$b-\delta$, $b-c$	0, 0

(2) *If* $b > c > 2\delta$, *an unfair collaboration situation exists such that the more a player wants to cooperate the more the opponent wants to defect when both players deviate from* $\{p^*, q^*\}$, *or vice versa, in which the cooperator will be worse off while the defector will be better off.*
(3) *If* $b < c < 2\delta$, *Tit-for-Tat is a stable optimal strategy for both players.*
(4) *If* $b > c$ *and* $c < 2\delta$, *cooperation is a stable optimal strategy for both players.*
(5) *If* $b < c$ *and* $c > 2\delta$, *defection is a stable optimal strategy for both players.*
(6) *If* $b = c$, *defection is a stable optimal strategy for both players as long as* $b - c/2 - \delta > 0$.
(7) *If* $\frac{b-c}{b-c/2-\delta} = 1$, *cooperation is a stable optimal strategy for both players as long as* $b - c/2 - \delta > 0$.

Proof. See Appendix.

First, Proposition 1(1) provides the conditions of the existence of a symmetric mixed-strategy Nash equilibrium. This is the unique mixed strategy if the conditions are satisfied. However, this proposition does not rule out the existence of pure-strategy Nash equilibrium. In fact, as shown in Proposition 1(2–5), pure strategies exist under different constrained conditions. Moreover, this symmetric mixed-strategy Nash equilibrium is not evolutionarily stable because when one player deviates, the other can be better off by deviating although neither player can be better off by deviating unilaterally. However, Proposition 1(1) gives us a good starting point, based on which we may more clearly observe the dynamics of the interaction between players. In reality, it is possible for players to maintain such a mixed-strategy equilibrium if we can treat the proportion of cooperation as the collaboration effort as shown in Table 3. In fact, the unstable property of the mixed-strategy Nash equilibrium is mostly due to the discrete-strategy game structure such that the payoff is linear to the probability of playing one strategy or the other. We will extend the discussion to a continuous e-collaboration game in the next section.

Comparing Table 1 with Table 4, we obtain the following equations: $T = b - \delta$, $R = b - c/2$, $S = b - c$, and $P = 0$. Proposition 1(2) has $b > c > 2\delta$, which suggests $T > R > S > P$, which is the condition of a SD game. That is to say, when $b > c > 2\delta$, the e-collaboration game becomes a SD game. Naturally, the property that {cooperate, defect} is the evolutionarily stable Nash equilibrium holds. Here we emphasize the dynamics of deviation from the symmetric mixed strategy to the {cooperate, defect} Nash equilibrium. Since $\{p^*, q^*\}$ is a Nash equilibrium, no player can be better off by deviating unilaterally from $\{p^*, q^*\}$. However, when one player deviates from $\{p^*, q^*\}$, it is better for the other to deviate to the opposite position. For example, if one player deviates to a higher collaboration effort by increasing p, the other player can be better off by choosing to fully defect. In fact, if either player has the right to move first, it is always for the first mover to defect. On the other hand, the follower should choose to fully cooperate if she/he is rational. This kind of SD games might well-suit a leader–follower model, although this kind of situation might not be fair because the follower looks like being forced to cooperate and the player who is more willing to cooperate has the disadvantage. This kind of situation could disappear in a continuous game when the payoff is not linear to the collaboration effort.

Another observation is regarding the social punishment δ. Proposition 1(1) implies that if δ is not big enough (e.g., $b > c > 2\delta$), the e-collaboration game is a case of the SD game. {*cooperate*, *defect*} and {*defect*, *cooperate*} are the two stable pure-strategy equilibria. To solve this dilemma, one approach is to enforce a higher social punishment cost, such as future cooperation opportunity cost, loss of reputation, etc., to alter the payoff matrix. As shown in Proposition 1(3) and (4), players' behaviors change when δ amounts to a certain level.

In Proposition 1(3), not only the social punishment δ is high, the cost to collaborate is also high such that $b < c < 2\delta$. Correspondingly, we have $R > T > P > S$, which is neither a PD condition nor a SD condition. Thus, we cannot apply the properties of PD or SD games to this situation directly. However, a Tit-for-Tat strategy follows. That is to say, if a player deviates from the original mixed strategy $\{p^*, q^*\}$ and wants to contribute more collaboration effort, the other player will follow the same strategy. Similar to PD games, {*defect*, *defect*} is a Nash equilibria. However, different from PD games, {*cooperate*, *cooperate*} is a evolutionarily stable Nash equilibrium. The reason is due to the social punishment. No player wants to defect when they reach the cooperation status because the loss due to the social punishment is larger than the gain from defecting. Notice that $b - c/2 > 0$, {*cooperate*, *cooperate*} is the only Pareto efficiency. Thus, there remains some negotiation room for players to improve their payoffs if they both choose to defer at the beginning.

Different from Proposition 1(3), Proposition 1(4) has $b > c$, which means that the collaboration cost is less than the benefit. This case is neither a PD nor a SD game. However, the social punishment is at least half of the collaboration cost. In this situation, if both players deviate simultaneously from $\{p^*, q^*\}$, the optimal strategy for both players is to cooperate. Thus {*cooperate*, *cooperate*} is the only evolutionarily stable Nash equilibrium. This shows the positive impact of social punishment, which pushes both players to fully cooperate.

As an opposite case to Proposition 1(4), Proposition 1(5) demonstrates a case that {*defect*, *defect*} is the only evolutionarily stable Nash equilibrium. In this case, the collaboration cost is too high while the social punishment is not big enough to force players to cooperate. Thus both players choose to defer when they deviate from $\{p^*, q^*\}$. From another perspective, this shows that social punishment has to be big enough to enforce a {*cooperate*, *cooperate*} Nash

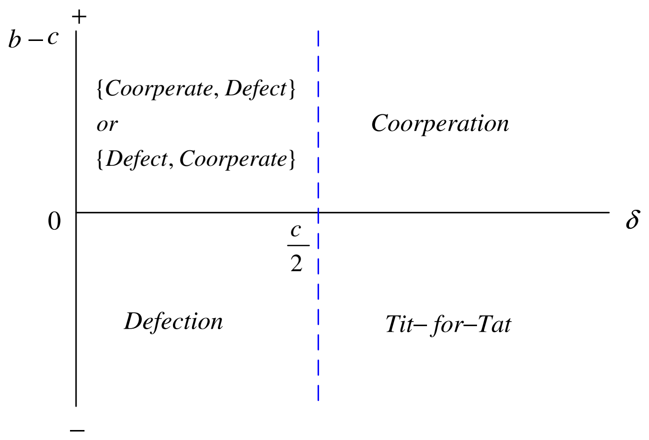

Fig. 1. Equilibria in an e-collaboration game.

equilibrium. Proposition 1(6) and (7) explain two boundary conditions.

Proposition 1 extends a symmetric SD game to a symmetric e-collaboration game with social punishment. The new game shows some properties that are not included in traditional PD and SD games. Proposition 1 also shows that the $\{cooperate, cooperate\}$ Nash equilibrium could be evolutionarily stable if the social punishment to the defector is big enough. Let us use Fig. 1 to illustrate the above situations. Overall, the lower social punishment, the higher chance the players will defect; on the other hand, the higher the social punishment, the higher the chance that the players will cooperate. The benchmark line is given by $\delta = \frac{c}{2}$.

Let us further use a numerical example to show the intuition of above results. Suppose two researchers are potentially to cooperate on a project. The benefit is $b = 10$ if they complete the project. First suppose the project is relatively easy, i.e., the cost is $c = 8$. If the social punishment is low, i.e., $\delta = 2 < 4 = \frac{c}{2}$, one research tends to lessen his/her collaboration effort if the other works hard. However, if the social punishment is high, i.e., $\delta = 6 > 4 = \frac{c}{2}$, such as losing their future cooperation opportunities or even friendship, both researchers tend to work hard. Then suppose the project is relatively tough, i.e., the cost is $c = 12$. Given that the social punishment is low, it is an equilibrium for both researchers to give up the project. However, given that the social punishment is high, if one researcher decides to go ahead or give up, the other will follow suit.

3.2. A continuous-strategy e-collaboration game

In the above discrete-strategy e-collaboration game, it might be far-fetched to define the proportional probability of playing the cooperation strategy as the collaboration effort. This problem can be solved by introducing the continuous-strategy e-collaboration game. According to Doebeli and Knowlton (1998), Doebeli et al. (2004), Killingback and Doebeli (2002), Wahl and Nowak (1999a), Wahl and Nowak (1999b), it is natural to assume that players adopt continuous strategies in PD and SD games. Similarly in an e-collaboration game, it is natural to assume that players can make continuously varying collaboration effort.

In a two-player e-collaboration game, we assume that each player has a maximum resource budget, x_m and y_m, respectively. However both players might determine their collaboration effort during the e-collaboration process. Let p be the effort index of Player 1 and q be the effort index of Player 2. Accordingly, px_m is the total collaboration effort of Player 1 and qy_m is the total collaboration effort of Player 2. We denote $B(px_m, qy_m)$ as common benefit of both players. Because of the efficiency of different players, we adopt $B(px_m, qy_m)$, which allows asymmetric efficiency between players as the benefit function. Let $C(px_m)$ and $C(qy_m)$ be the cooperation costs of both players respectively. Thus, Player 1's payoff function can be written as follows.

$$\Pi_1(p, q) = B(px_m, qy_m) - C(px_m). \tag{6}$$

Similarly, Player 2's payoff is

$$\Pi_2(p, q) = B(px_m, qy_m) - C(qy_m). \tag{7}$$

Here we would like to emphasize that we are discussing an asymmetric continuous e-collaboration game, which is different from the symmetric model in Doebeli et al. (2004) who utilize a benefit function $B(px_m + qy_m)$. First, x_m could be different from y_m and p could be different from q. Second, Player 1 may not be as efficient as Player 2 in contributing to the collaboration result. If Eqs. (6) and (7) are concave and we obtain a pair of $\{p^*, q^*\}$ where $0 \leqslant p \leqslant 1$ and $0 \leqslant q \leqslant 1$, then $\{p^*, q^*\}$ is a unique equilibrium for this asymmetric continuous e-collaboration game.

We first focus on cases where the payoff functions are linear to the collaboration efforts. We have the following observation.

Proposition 2. *A two-person discrete-strategy e-collaboration game with mixed strategies can be described equivalently by a two-person continuous-strategy e-collaboration game with a payoff function linear to their collaboration efforts and a correlated item* px_mqy_m.

Proof. See Appendix.

Proposition 2 shows that we can use a two-person continuous-strategy e-collaboration game with a payoff function linear to their collaboration efforts and a correlated item px_mqy_m to represent a two-person discrete-strategy e-collaboration game with mixed strategies. This also partially supports our previous claim that the proportional probability of choosing the cooperation strategy can be considered as the collaboration effort. From another perspective, a two-person continuous-strategy e-collaboration game with linear collaboration efforts and a correlated item px_mqy_m may have properties similar to a two-person discrete-strategy e-collaboration game.

In contrast, a two-person continuous-strategy e-collaboration game with a payoff function nonlinear to their collaboration efforts could be quite different from a discrete-strategy e-collaboration game. In this article, we consider a quadratic payoff function. The dynamics of a continuous e-collaboration game could be richer because of the quadratic cost and benefit functions.

Consider the following game:

$$B(px_m, qy_m) = \alpha_1(px_m)^2 + \alpha_2 px_m + \beta_1(qy_m)^2 + \beta_2 qy_m + \lambda px_m qy_m, \quad (8)$$

$$C(px_m) = c_1(px_m)^2 + c_2 px_m, \quad (9)$$

$$C(qy_m) = d_1(qy_m)^2 + d_2 py_m. \quad (10)$$

So, Player 1's payoff function is

$$\Pi_1(p,q) = \alpha_1(px_m)^2 + \alpha_2 px_m + \beta_1(qy_m)^2 + \beta_2 qy_m + \lambda px_m qy_m - c_1(px_m)^2 - c_2 px_m. \quad (11)$$

Player 2's payoff function is

$$\Pi_2(p,q) = \alpha_1(px_m)^2 + \alpha_2 px_m + \beta_1(qy_m)^2 + \beta_2 qy_m + \lambda px_m qy_m - d_1(qy_m)^2 - d_2 qy_m. \quad (12)$$

Thus, we have the following proposition.

Proposition 3. *If a two-person continuous-strategy e-collaboration game has quadratic payoffs as provided by Eqs. (8)–(10), and* $\alpha_1 < c_1$ *and* $\beta_1 < d_1$, *then* $\{p^*, q^*\}$ *is the unique and stable Nash equilibrium given that* $0 \leqslant p^* \leqslant 1$ *and* $0 \leqslant q^* \leqslant 1$ *where*

$$p^* = \frac{2(\alpha_2 - c_2) - \frac{\lambda(d_2-\beta_2)}{d_1-\beta_1}}{4(c_1-\alpha_1) - \frac{\lambda^2}{d_1-\beta_1}} \frac{1}{x_m}, \quad (13)$$

and

$$q^* = \frac{2(\beta_2 - d_2) - \frac{\lambda(c_2-\alpha_2)}{c_1-\alpha_1}}{4(d_1-\beta_1) - \frac{\lambda^2}{c_1-\alpha_1}} \frac{1}{y_m}. \quad (14)$$

Proof. See Appendix.

In Proposition 3, $\alpha_1 < c_1$ and $\beta_1 < d_1$ give us two concave payoff functions (11) and (12). So if $0 \leqslant p^* \leqslant 1$ and $0 \leqslant q^* \leqslant 1$, $\{p^*, q^*\}$ is the unique and stable Nash equilibrium for this two-person continuous-strategy e-collaboration game. Notice that if all parameters fixed, for Player 1, p decreases when x_m increases; however, the overall effort px_m is constant. The same is true for Player 2. It implies that an individual will more likely to fully cooperate when his/her budget for the e-collaboration is smaller, or vice versa.

$0 \leqslant p^* \leqslant 1$ and $0 \leqslant q^* \leqslant 1$ require $0 \leqslant (\alpha_2 - c_2) + \lambda q y_m \leqslant 2(c_1 - \alpha_1)x_m$ and $0 \leqslant (\beta_2 - d_2) + \lambda p x_m \leqslant 2(d_1 - \beta_1)y_m$. If we do not have $0 \leqslant p^* \leqslant 1$ and $0 \leqslant q^* \leqslant 1$, we might have to consider boundary conditions and Proposition 3 does not hold. Suppose $\alpha_1 < c_1$ and $\beta_1 < d_1$ continue to be true. Here are several special cases:

(1) If $p^* < 0$ and $q^* < 0$, then $p^o = 0$ and $q^o = 0$, that is similar to {*defect*, *defect*} in discrete-strategy e-collaboration games, are the optimal strategies for the players. Where p^o and q^o are the new optimal strategies.
(2) If $0 \leqslant p^* \leqslant 1$ and $q^* < 0$, it is optimal for Player 2 to fully defect (i.e. $q^o = 0$) while Player 1 plays her/his optimal strategy $p^o = \frac{(\alpha_2-c_2)}{2(c_1-\alpha_1)x_m}$.
(3) If $0 \leqslant p^* \leqslant 1$ and $q^* > 1$, it is optimal for Player 2 to fully cooperate (i.e. $q^o = 1$) while Player 1 plays her/his optimal strategy $p^o = \frac{(\alpha_2-c_2)+\lambda y_m}{2(c_1-\alpha_1)x_m}$.
(4) If $p^* > 1$ and $q^* > 1$, then $p^o = 1$ and $q^o = 1$, that is similar to {*cooperate*, *cooperate*} in discrete-strategy e-collaboration games, are the optimal strategies for the players.

Similar discussion can be extended to cases such as $p^* > 1$ and $0 \leqslant q^* \leqslant 1$ and those cases where payoff functions (11) and (12) are no longer concave.

From Eqs. (13) and (14), we can infer that the higher α_1 and α_2, the higher p^*. Similarly, the higher β_1 and β_2, the higher q^*. In summary, we have

Proposition 4. *The higher profit the players can gain from the collaboration, the more collaboration effort they will contribute.*

On the other hand, the higher c_1 and c_2, the lower p^*. Similarly, the higher d_1 and d_2, the lower q^*. Thus,

Proposition 5. *The higher cost to the players, the less collaboration effort they will contribute.*

In the above discussion, we implicitly include the social punishment in the cost. Now, let us explicitly introduce a model of the social punishment in this continuous-strategy e-collaboration game. Specifically, considering the social punishment, (9) and (10) are transformed to

$$C(px_m) = c_1(px_m)^2 + c_2 px_m + (1-p)\delta x_m, \quad (15)$$

$$C(qy_m) = d_1(qy_m)^2 + d_2 py_m + (1-q)\delta y_m. \quad (16)$$

In the above equations, δ is denoted as the unit social punishment cost. The less the collaboration effort, the higher the social punishment cost to the specific player. We would like to point out that the real social punishment cost could be different although this model assumes that the social punishment cost is proportional to the collaboration effort and x_m or y_m. Here we focus on the interaction mechanism between the social punishment cost and the collaboration effort rather than the concrete values. Thus, Player 1's payoff function is

$$\Pi_1(p,q) = \alpha_1(px_m)^2 + \alpha_2 px_m + \beta_1(qy_m)^2 + \beta_2 qy_m + \lambda px_m qy_m - c_1(px_m)^2 - c_2 px_m - (1-p)\delta x_m.$$

Player 2's payoff function is

$$\Pi_2(p,q) = \alpha_1(px_m)^2 + \alpha_2 px_m + \beta_1(qy_m)^2 + \beta_2 qy_m + \lambda px_m qy_m - d_1(qy_m)^2 - d_2 qy_m - (1-q)\delta y_m.$$

Similar to Proposition 3, we gain

$$p^* = \frac{2(\alpha_2 - c_2 + \delta) - \frac{\lambda(d_2-\beta_2-\delta)}{d_1-\beta_1}}{4(c_1-\alpha_1) - \frac{\lambda^2}{d_1-\beta_1}} \frac{1}{x_m} \quad (17)$$

and

$$q^* = \frac{2(\beta_2 - d_2 + \delta) - \frac{\lambda(c_2-\alpha_2-\delta)}{c_1-\alpha_1}}{4(d_1-\beta_1) - \frac{\lambda^2}{c_1-\alpha_1}} \frac{1}{y_m}. \quad (18)$$

The above solution $\{p^*, q^*\}$ is the unique and stable Nash equilibrium if $\alpha_1 < c_1$ and $\beta_1 < d_1$ and if $0 \leqslant p^* \leqslant 1$ and $0 \leqslant q^* \leqslant 1$. We can infer from the above equation that

Proposition 6. *In a two-person continuous-strategy e-collaboration game, the higher the unit social punishment cost is, the higher the collaboration effort the player will contribute.*

This proposition delivers a similar message to Proposition 1 that the social punishment needs to be big enough to enforce a $\{cooperate, cooperate\}$ Nash equilibrium. In (17), letting $p^* = 1$ yields

$$\delta_1 = \frac{2(c_2 + 2x_m(c_1-\alpha_1) - \alpha_2)(d_1-\beta_1) + \lambda(d_2 - \lambda x_m - \beta_2)}{\lambda + 2d_1 - 2\beta_1}.$$

Similarly, letting $q^* = 1$ yields

$$\delta_2 = \frac{2(d_2 + 2y_m(d_1-\beta_1) - \beta_2)(c_1-\alpha_1) + \lambda(c_2 - \lambda y_m - \alpha_2)}{\lambda + 2c_1 - 2\alpha_1}.$$

Thus, we have

Corollary 7. *If* $\delta \geqslant \max\{\delta_1, \delta_2\}$, *then* $\{cooperate, cooperate\}$ *is the Nash equilibrium in a two-person continuous-strategy e-collaboration game.*

Since there are infinite possible configurations of this continuous-strategy e-collaboration game, we constraint our numerical analysis to a special scenario, called *Expert–Apprentice* collaboration game, to partially illustrate the above discussion. We assume that the expert is more knowledgeable ($x_m = 2$) and more efficient ($\alpha_2 = 1.5$) than the apprentice ($y_m = 1$ and $\beta_2 = 1$). The remaining configuration is given by $\alpha_1 = 1$, $\beta_1 = 1$, $c_1 = 2$, $c_2 = 1$, $d_1 = 2$, $d_2 = 1$, $\delta = 1$. We illustrate the sensitiveness analysis of p and q with respect to λ in Fig. 2 and $\Pi_1(\lambda)$ and $\Pi_2(\lambda)$ with respect to λ in Fig. 3. In the context, λ can be interpreted as the collaboration efficiency. At the beginning, the expert has to teach the apprentice; as a result, the collaboration efficiency is low, i.e., $\lambda < 0$. If the collaboration efficiency is so low that the apprentice might be reluctant to learn; however, over time, the collaboration efficiency increases, the apprentice increasingly becomes more interested in working with the expert. As λ grows bigger and bigger, both the expert and the apprentice are more willing to work together. Since the apprentice is learning from the expert, the apprentice obtains positive payoff from the beginning. On the other hand, the expert might obtain negative payoff from the cooperation if the collaboration efficiency is low since the expert has a high expectation about the quality of the work. The expect starts to receive positive payoff when the collaboration efficiency is high enough such that the expert's expectation of higher quality is satisfied. A good example of this might be the learning process of a Ph.D. student under instruction of his/her advisor.

As Proposition 6 suggests, the higher the social punishment cost, the higher the chance that the players will cooperate. Based on the above Expert–Apprentice collaboration game, the social punishment cost required to mandate a full cooperation from both players varies as shown in Fig. 4. It shows that the required δ decreases when the two players work together more efficiently.

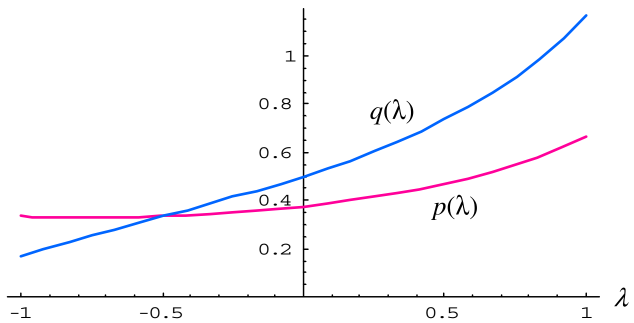

Fig. 2. Sensitiveness analysis of p and q w.r.t. λ.

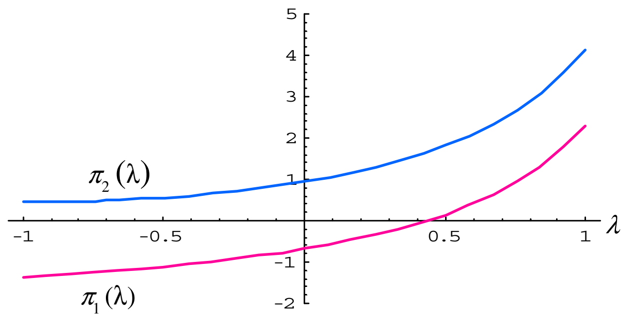

Fig. 3. Sensitiveness analysis of $\Pi_1(\lambda)$ and $\Pi_2(\lambda)$ w.r.t. λ.

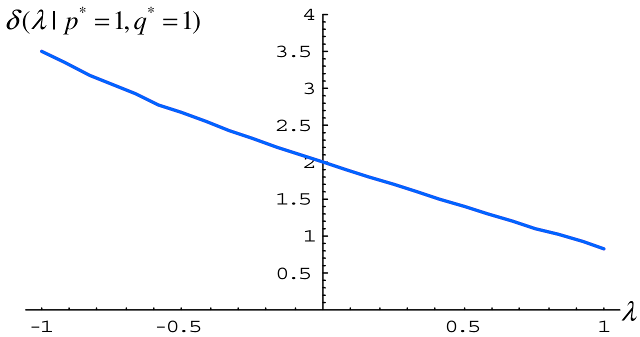

Fig. 4. The value of δ to mandate a full cooperation.

3.3. A continuous-strategy e-collaboration game with incomplete information

The above discrete-strategy and continuous-strategy e-collaboration games implicitly assume complete information of the payoff functions. In reality, players might not know the payoff parameters of other players even if we assume that each player knows his/her own payoff parameters. For example, in Eq. (8), Player 1 knows the parameters α_1, x_m, α_2, and λ, but he/she cannot know β_1, q, y_m, and β_2. On the other hand, it is common to assume that a player can estimate the collaboration effort of the other player. For example, a player can have a belief function of the other player's collaboration effort. We denote θ as the belief of the other player's collaboration effort and denote $f(\theta)$ as the probability density function of the belief. In this game setting, we also assume that the game is multi-stage such that players can play the game several rounds. Thus, the later rounds can infer the belief function from previous moves of the other players.

The complexity of computing optimal strategies in this dynamic e-collaboration game with incomplete information lies in the payoff function. Other than assuming that payoff function is an irregular function of the collaboration, we continue to assume that players have payoffs function as shown in (11) and (12) but players do not know the parameters of the other player except λ. As a result, we cannot utilize Eqs. (13) and (14) directly in this situation. However, the first-order conditions of (11) and (12) give us

$$p = \frac{(\alpha_2 - c_2) + \lambda q y_m}{2(c_1 - \alpha_1)x_m} \tag{19}$$

and

$$q = \frac{(\beta_2 - d_2) + \lambda p x_m}{2(d_1 - \beta_1)y_m}. \tag{20}$$

Since (21) and (22) are independent from the other player's payoff parameters, we may develop the solutions for the incomplete information cases as following:

$$p = \int_0^{\infty} \frac{(\alpha_2 - c_2) + \lambda\theta(qy_m)}{2(c_1 - \alpha_1)x_m} f(\theta(qy_m))\mathrm{d}\theta(qy_m) \tag{21}$$

and

$$q = \int_0^{\infty} \frac{(\beta_2 - d_2) + \lambda\theta(px_m)}{2(d_1 - \beta_1)y_m} f(\theta(px_m))\mathrm{d}\theta(px_m). \tag{22}$$

If $0 \leqslant p \leqslant 1$ and $0 \leqslant q \leqslant 1$, the solution could converge to $\{p^*, q^*\}$, which are the same as (13) and (14). And the discussion of the collaboration effort will be similar to that in previous section.

In this multi-stage e-collaboration game, players can learn their opponent's collaboration effort from the previous move. Thus, players can update their belief functions. If both payoff functions are concave in $0 \leqslant p \leqslant 1$ and $0 \leqslant q \leqslant 1$ and $\lambda > 0$, the more a player cooperates, the more the other player will cooperate. Whether a player will fully cooperate depends on the budget of the other player. A special case could be that one player fully cooperates when the other just partially contributes to the collaboration. This occurs if $0 < p = \frac{(\alpha_2 - c_2) + \lambda y_m}{2(c_1 - \alpha_1)x_m} < 1$ and $1 = q = \frac{(\beta_2 - d_2) + \lambda \frac{(\alpha_2 - c_2) + \lambda y_m}{2(c_1 - \alpha_1)}}{2(d_1 - \beta_1)y_m}$.

4. Media selection in e-collaboration games

Research on electronic communication media use by individuals suggests that those media suppress key elements normally present in unconstrained face-to-face interaction (George and Carlson, 2005; Graetz et al., 1998; DeRosa et al., 2004). This notion is often associated with a widely cited theoretical framework in the field of e-collaboration known as media richness theory (Barkhi, 2005; Daft and Lengel, 1986; Daft et al., 1987; Lengel and Daft, 1988).

While influential among communication media researchers, media richness theory has been often criticized because of its deterministic nature (El-Shinnawy and Markus, 1998; Markus, 1994). One of the criticisms is that the theory makes deterministic predictions regarding media choice and task outcome quality based on the degree of equivocality, or complexity, of tasks (Daft and Lengel, 1986).

Media richness theorists view e-mail as a significantly less rich communication medium than the face-to-face medium. The medium created by the telephone is seen as somewhere in between e-mail and face-to-face in terms of richness. It is predicted by media richness theory that the use of a lean medium for communication in connection with an equivocal task (e.g., new product development) generally leads to a lower quality outcome than the use of a richer medium.

However, several empirical findings are inconsistent with the above prediction (Burke and Aytes, 2001; Dennis and Kinney, 1998). Some empirical findings suggest media effects that are the opposite of those predicted (Kock, 1998). In other words, empirical findings exist indicating that media of low richness, when used in equivocal tasks, may, in fact, have a positive impact on task outcome quality. A number of theoretical models have been presented as replacements for, or extensions to, media richness theory to address these and other related inconsistencies between the theory and empirical findings. The media naturalness model is one such model (DeRosa et al., 2004; Kock, 2004; Kock, 2005).

Proponents of the media naturalness model argue that the human brain has been designed by Darwinian evolution to excel in face-to-face interaction (DeRosa et al., 2004; Kock, 2005). Consequently, communication media that suppress face-to-face communication elements are presented by the model as posing cognitive obstacles to natural communication. Natural face-to-face communication elements include the ability to employ facial expressions and tone of voice in communication interactions. Those elements also include the ability to provide and receive immediate feedback (e.g., through body language) on what is being communicated.

The media naturalness model differs from media richness theory in one main respect, which makes the model appear to be somewhat counterintuitive. The media naturalness model does not predict that media choice or task outcome quality is determined by a medium's degree of naturalness. Instead, the model suggests that the extra cognitive effort posed by the use of a less natural medium will trigger a phenomenon called compensatory adaptation. This phenomenon is characterized by individuals adaptively modifying their communicative behavior in order to overcome the obstacles posed by the lack of naturalness of a medium. According to the media naturalness model, the outcomes following such compensatory adaptation may be actually better than those achieved through a more natural communication medium (Kock, 1998).

To put it differently, communication media of low naturalness are viewed in the media naturalness model as causing an increase in the cognitive effort spent in communication interactions. This may in turn lead to better task quality outcomes under some circumstances, and to identical or worse outcomes in others. A study by Ocker et al. (1995) provides a particularly compelling set of data in support of this assumption.

The issue of media selection in e-collaboration has not been investigated from a game-theoretical perspective. Barkhi (2005) studies the behavior of the members in group decision making systems using a cooperative game theory concept. Different from Barkhi (2005), this article presents an analytic framework from a non-cooperative game-theoretical perspective with explicit consideration of the impact of social punishment. On the other hand, the concept of "defect" in this article is designated to be associated with the overall collaboration effort rather than any specific media, which is different from George and Carlson (2005) and George and Marett (2005) that explain why people choose to deceive in specific media. More specifically, this article does not explicitly compare the richness or naturalness of media but provides an analytic framework for media selection in an e-collaboration game. We assume that the effectiveness of media is known, the collaborators want to know how to integrate the effectiveness of media, and the time-varying adaptive effects of these media into the previously discussed e-collaboration games.

To simplify the discussion, suppose there are two alternative communication media, for example, telephone and e-mail. In a specific e-collaboration game, players can choose to use telephone or e-mail but not both. The following is the payoff matrix of a media selection e-collaboration game. Since players have different preference toward the media, μ_1 could be different from μ_2 and so could be v_1 and v_2 (see Table 5).

Table 5
A media selection game for a component collaboration task

Player 1	Player 2	
	Telephone	e-Mail
Telephone	μ_1, μ_2	0, 0
e-Mail	0, 0	v_1, v_2

In the above media selection game, both {*telephone*, *telephone*} and {*e-mail*, *e-mail*} are the Nash equilibria. That is to say, if one player chooses telephone, it is optimal for the other player to choose telephone too. However, due to the properties of some component tasks, a specific medium will be better than another medium for both players, for example, $\mu_1 > v_1$ and $v_1 > v_2$. Although {*e-mail*, *e-mail*} is still a Nash equilibrium, {*telephone*, *telephone*} is a better choice for both players. Thus, in this situation, we use Pareto efficiency to refine the Nash equilibrium and {*telephone*, *telephone*} will be a better solution for both players. For the rest of situations, such as $\mu_1 > v_1$ but $v_1 < v_2$, the final ex-post result will be determined by which medium be proposed at first by either player. Leadership or other characteristics of the players might play an role in the selection process. For example, if one player is the leader or is more active in the collaboration, this player may choose the medium first and the other will follow. Some focal effect, such as one player always lets the other make the choice at first, will affect the result as well.

Typically, a project may involve many sub-projects, called component tasks in this article. The media selected for some component tasks could be different from those selected for others. E.g., players using telephone for some component tasks and e-mail for other component tasks, because one medium might be more efficient than another for some component tasks. We call this phenomenon *media relativeness*. That is, an individual medium may not be more efficient than another for a specific component task, and thus the selection of a medium will be relative to the preference matrix for both players in the game. Allowing both players to use different media in component tasks, rather than using a single medium throughout the whole collaboration task, could improve the overall performance for them. The dynamics of media selection can be more complex if we assume that a player's preferences toward media change over time. Arguably players have different learning curves, and thus adapt differently to a given medium. Predetermined payoffs may not apply as a player gradually learns how to adapt to a medium, and to another player using the medium, in order to utilize the medium to its maximum capability (Kock, 2005b). Due to this individual player adaptation phenomenon, a player's original choice of a specific medium for some component tasks could shift to other media over time.

We assume the existence of an adaptive effect that takes place as the collaborators use a particular medium. The effect essentially is that the more the collaborators use the same medium, the more effective they become at using the medium. Hence, we assume a piece-wise linear learning curve for the collaborators as a result of the adaptive effect, whose slope is denoted by $1 + l_{\imath,\jmath}$, where $\imath$ stands for the specific medium and $\jmath$ stands for the cumulative frequency of Medium $\imath$ being utilized by the collaborators previously. We define $l_{\imath,0} = 0\ \forall \imath$. The sum of $\jmath$ for all media equals the total number of component games played until the current round (component game). We assume that the collaborators have the same $l_{\imath,\jmath}$. As we have shown that it is better for collaborators to use the same medium in a component game, we assume that collaborators will use the same medium in a component game, and thus, $\jmath$ of Medium $\imath$ remains the same for all collaborators. For example, suppose we have two media. If collaborators use Medium 1 in the first round, the $\jmath$ for Medium 1 will become 1 in the game settings in the second round; however, the $\jmath$ for Medium 2 remains at 0 in the second round.

We first consider a discrete-strategy model. As we show in Section 3.1, the symmetric e-collaboration game in Table 4 is designed for a single medium. When there are multiple media, collaborators might gain different payoffs due to the selection of a specific medium. Thus, for Medium $\imath$, the two-player discrete e-collaboration game as shown in Table 4 is transformed to Table 6. In Table 6, $1 + l_{\imath,\jmath}$ is the adaptive effect. Here we continue to assume that both players share the common benefit and cost results. However, $l_{\imath,\jmath}$ might differ among all possible media. $\jmath$ for a specific medium, e.g., Medium $\imath$, will increase by 1 whenever this medium is utilized once in previous component games.

Suppose the overall collaboration tasks are divided into a series of component games, in which collaborators might choose different media for each component game. Thus, the expected payoff of Player 1 in the tth component game of this dynamic collaboration game can be expressed as

$$\begin{aligned}\Pi_t(p,\imath) = \max\nolimits_{p,\imath}\{&pq[(1+l_{\imath,})b_\imath - c_\imath/2] \\ &+ p(1-q)[(1+l_{\imath,})b_\imath - c_\imath] \\ &+ (1-p)q[(1+l_{\imath,})b_\imath - \delta] + \Pi_{t-1}(p,\imath)\},\end{aligned} \tag{23}$$

where $\Pi_{t-1}(p,\imath)$ is the expected payoff from the previous round, and the other items before $\Pi_{t-1}(p,\imath)$ stand for the expected payoff in the current round which is similar to Eq. (1) but related with Medium $\imath$. We assume $\Pi_0 = 0$. The value of $\jmath$ will increase by 1 from the value of the same medium in $\Pi_{t-1}(p,\imath)$. Similarly, the expected payoff of Player 2 is given by

$$\begin{aligned}\Pi_t(q,\imath) = \max\nolimits_{q,\imath}\{&pq[(1+l_{\imath,})b_\imath - c_\imath/2] + q(1-p)[(1+l_{\imath,})b_\imath \\ &- c_\imath] + (1-q)p[(1+l_{\imath,})b_\imath - \delta] + \Pi_{t-1}(q,\imath)\}.\end{aligned}$$

Table 6
A symmetric e-collaboration game for Medium $\imath$

Player 1	Player 2	
	Cooperate	Defect
Cooperate	$(1+l_{\imath,\jmath})b_\imath - c_\imath/2$, $(1+l_{\imath,\jmath})b_\imath - c_\imath/2$	$(1+l_{\imath,\jmath})b_\imath - c_\imath$, $(1+l_{\imath,\jmath})b_\imath - \delta$
Defect	$(1+l_{\imath,\jmath})b_\imath - \delta$, $(1+l_{\imath,\jmath})b_\imath - c_\imath$	0, 0

Table 7
Telephone: $t = 1$

Player 1	Player 2	
	Cooperate	Defect
Cooperate	6, 6	2, 5
Defect	5, 2	0, 0

Table 8
Telephone: $t = 2$

Player 1	Player 2	
	Cooperate	Defect
Cooperate	6, 6	2, 5
Defect	5, 2	0, 0

This is a typical dynamic programming problem. An enumerative approach to find the optimal solutions is to compute the $\{p^*, q^*\}$ for every $\imath$ and then to find the optimal combination of a series of different media among all component games. In general the computation complexity will be NP-hard. However, if the number of all component games is a small number and the number of media is also small, the optimal collaboration effect and the optimal selection of the media in each component games could be still computable in reasonable time.

We illustrate the above discussion with a small two-stage game. Suppose the e-collaborators have two options: telephone vs. e-chatting such as MSN and Yahoo! Messenger. Continuing from the numeric example at the end of Section 3.1, we assume that there is no learning curve in using the telephone, but the efficiency can increase $l_{\imath,\jmath} = 50\%$ if the players use the e-chatting the second time. Let $b = 10$, $c = 8$, $\delta = 5$ for using telephone and $b = 8$, $c = 6$, $\delta = 5$ for using the telephone the first time. Hence, we have the following game settings as illustrated in Tables 7–10. This example demonstrates that it is an optimal strategy for both players to cooperate using e-chatting in this two-stage game since $5 + 9 > 6 + 6$ although the telephone outperforms the e-chatting in a single round. The above example is straightforward because $\{cooperate, cooperate\}$ is a dominant strategy in each single-stage game for any medium. Similar to the result in Section 3.1, it is easy to infer that the higher the social punishment cost, the higher the chance that the player will cooperate.

We now briefly describe a dynamic continuous-strategy game. Player 1's payoff function can be written as following:

$$\begin{aligned}\Pi_t(p,\imath) = \max\nolimits_{p,\imath}\{&(1+l_{\imath,})B(px_m, qy_m)_\imath - C(px_m)_\imath \\ &+ \Pi_{t-1}(p,\imath)\}.\end{aligned} \tag{24}$$

In Eq. (24), $\Pi_{t-1}(p,\imath)$ is the expected payoff gained from the previous round. The expected payoff in the current

Table 9
e-Chatting: $t = 1$

Player 1	Player 2	
	Cooperate	Defect
Cooperate	5, 5	2, 3
Defect	3, 2	0, 0

Table 10
e-Chatting: $t = 2$

Player 1	Player 2	
	Cooperate	Defect
Cooperate	9, 9	6, 7
Defect	7, 6	0, 0

round depends on the benefit $B(px_m, qy_m)_\iota$ and cost functions $C(px_m)_\iota$. The expected payoff for Player 2 is given by

$$\Pi_\iota(q,\iota) = \max_{q,\iota}\{(1 + l_{\iota,})B(px_m, qy_m)_\iota - C(qy_m)_\iota + \Pi_{t-1}(q,\iota)\}. \quad (25)$$

Basically, players need to find out the optimal collaboration effort for every medium in each round. If the information about the opponent is complete like in Section 3.2, the computation might be easier than an incomplete information case like in Section 3.3. However, this is also a dynamic programming problem, and the computation complexity is expected to be NP-hard. Some heuristic algorithms can be found in Bertsekas (2000) and Cormen et al. (2001).

5. Conclusion

In this article, we utilize evolutionary game theory to analyze the strategic interaction between two players in an e-collaboration game. The analysis includes a look at collaboration effort and communication media selection by the players. We first extend the traditional Prisoners' Dilemma and Snowdrift game theory to discrete-strategy e-collaboration games by explicitly including social punishments into players' payoff functions. Social punishments could include loss of reputation, shadow of future collaboration, ethic effects, and other social and psychological influences. We show that the social punishment should be large enough to enforce a full cooperation in symmetric discrete-strategy e-collaboration games. If the social punishment is not significant, the first to defect could have the advantage and the other collaborator will be forced to provide full effort if he/she behaves rationally. When the social punishment becomes more than half of the collaboration cost, it is evolutionarily stable for both players to cooperate. In some situations a Tit-for-Tat strategy is arguably the optimal strategy for both players. One example would be when the total benefit is less than the collaboration cost, and the social punishment is more than half of the collaboration cost. In continuous-strategy e-collaboration games, asymmetric strategies, in which players contribute different collaboration effort levels, could exist. Similar to the symmetric discrete-strategy e-collaboration games, if the social punishment cost is significant enough, a full collaboration is the Nash equilibrium for the players in the continuous-strategy e-collaboration games. In a setting with incomplete information, given that the payoff functions are quadratic, one player can learn from previous moves of the other player and update their collaboration efforts in future moves. A dynamic media selection game is a more complicated e-collaboration game, in which the payoff functions between two players are affected by the impact of different media. Based on the preferences of the players, we argue that players could adopt different media in different component collaboration tasks, and thus the selection of media in an e-collaboration is associated with the expected payoff in the overall e-collaboration tasks. Considering the adaptive effect, characterized by players becoming better at using certain media over time, we can conclude that players might select different media for different component tasks during the e-collaboration process.

In the future, the research outlined in this article could be extended in several directions, of which three are particularly noteworthy. First, this research could be extended with a focus on the identification of common e-collaboration payoff functions in various types of tasks. Second, a multi-player e-collaboration game extension of this research could be developed and discussed based on real-world situations; most of which are likely to involve multiple players. Finally, this research could be extended through the design and execution of empirical studies addressing the theoretical properties of the frameworks developed and discussed here.

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Appendix

Proof of Proposition 1. Given that $b - c/2 - \delta \neq 0$, for Proposition 1(1), it is easy to prove that $b \geqslant c \geqslant 2\delta$ if both $b - c \geqslant 0$ and $b - c/2 - \delta > 0$ conditional on $\frac{b-c}{b-c/2-\delta} \leqslant 1$. Similarly, we have $b \leqslant c \leqslant 2\delta$ if both $b - c \leqslant 0$ and $b - c/2 - \delta < 0$ conditional on $\frac{b-c}{b-c/2-\delta} \leqslant 1$. So, according to (3), either player cannot be better off if $0 \leqslant p^*, q^* \leqslant 1$.

Now we prove Proposition 1(2). If $b > c > 2\delta$, Proposition 1(1) concludes that $\{p^*, q^*\}$ is a Nash equilibrium. Due to the symmetric game assumption, similar to Eq. (3), we obtain

$$\frac{\partial \Pi_2(q)}{\partial q} = b - c - p(b - c/2 - \delta).$$

From Proposition 1(1), $b > c > \delta$ suggests $b - c/2 - \delta > 0$. Thus, when p increases, which means that Player 1 wants to increase cooperation effort, $\frac{\partial \Pi_2(q)}{\partial q}$ decreases to be below 0. Thus, it is optimal for Player 2 to reduce the level of the cooperation; as a result, q decreases to zero. However, when q decreases, $\frac{\partial \Pi_1(p)}{\partial p}$ becomes positive so that it is optimal for Player 1 to increase p continuously. Finally, one player is to fully cooperate while the other is to fully defect, which is also a Nash equilibrium.

To see the change of the payoffs, let us start with a player's original payoff function when both players use $\{p^*, q^*\}$ in Proposition 1(1).

$$\begin{aligned}\Pi_1(p) &= pq(b-c/2) + p(1-q)(b-c) + (1-p)q(b-\delta)\\ &= p[(b-c) + q(b-c/2-b+c)] + (1-p)q(b-\delta)\\ &= p[(b-c) + qc/2] + (1-p)q(b-\delta)\\ &= p(b-c) + q(b-\delta) + pq(c/2+\delta-b).\end{aligned}$$

From Proposition 1(1), we know $p^* = q^* = \frac{b-c}{b-c/2-\delta}$. Substituting p and q with p^* and q^* results in

$$\begin{aligned}\Pi_1(p^*) &= \frac{b-c}{b-c/2-\delta}(b-c) + \frac{b-c}{b-c/2-\delta}(b-\delta)\\ &\quad - \frac{b-c}{b-c/2-\delta}\,\frac{b-c}{b-c/2-\delta}(c/2+\delta-b)\\ &= \frac{(b-c)(b-\delta)}{b-c/2-\delta}.\end{aligned}$$

Because $b > c > 2\delta$, we obtain $\Pi_1(p^*) < b-\delta$, which implies that the cooperator will be worse off if he/she deviates from the original Nash equilibrium and is willing to cooperate but the other player defects. Meanwhile, we obtain $\Pi_1(p^*) > b-c$, from which we can infer that the defector will be better off when he/she deviate from the original Nash equilibrium and the other player becomes cooperator.

Now we prove Proposition 1(3). If $b < c < 2\delta$, $\frac{\partial \Pi_2(q)}{\partial q}$ increases when p increases. As a result, it is better for the opponent to increase q. Thus, both players will choose to cooperate. From the proof of Proposition 1(2), we know $\Pi_1(p^*) < b-c < b-c/2$ if $b < c < 2\delta$. Thus, we can conclude that both players will be better off if they choose to deviate from $\{p^*, q^*\}$ simultaneously and to cooperate when $b < c < 2\delta$.

Similarly, if p decreases then $\frac{\partial \Pi_2(q)}{\partial q}$ becomes negative. Thus, it is better for the opponent to defect too. Furthermore, we have $\Pi_1(p^*) < b-c < 0$ if $b < c < 2\delta$. This result suggests that both players will be better off if they choose to deviate from $\{p^*, q^*\}$ simultaneously and to defect when $b < c < 2\delta$. In summary, Tit-for-Tat is the optimal strategy for both players if $b < c < 2\delta$.

Now let us prove Proposition 1(4). $b > c$ and $c < 2\delta$ result in $b-c > 0$ and $b-2\delta < 0$. Furthermore, we have $b-2\delta < b-c/2-\delta < b-c$. Thus, $b-c/2-\delta$ ranges from a negative value to a positive value. If $b-c/2-\delta > 0$, we obtain p^*, $q^* > 1$. However, p^*, $q^* > 1$ is impossible because a probability cannot be more than 1. Together with Eq. (3), we know $\frac{\partial \Pi_1(p)}{\partial p} > 0$ and $\frac{\partial \Pi_2(q)}{\partial q} > 0$ and thus p^*, $q^* = 1$ is a stable Nash equilibrium for both players. On the other hand, if $b-c/2-\delta < 0$, from Eqs. (4) and (5), we get p^*, $q^* < 0$, which is also impossible. Given that $\frac{\partial \Pi_1(p)}{\partial p} > 0$ and $\frac{\partial \Pi_2(q)}{\partial q} > 0$ unconditionally, both players will be better off by choosing to cooperate.

Proposition 1(5) is a reversed version of Proposition 1(4). $\delta < c/2$ yields $b-c < b-c/2-\delta$. If $b-c < b-c/2-\delta < 0$, we obtain p^*, $q^* > 1$. Different from Proposition 1(4), we get $\frac{\partial \Pi_1(p)}{\partial p} < 0$ and $\frac{\partial \Pi_2(q)}{\partial q} < 0$. Thus, both players will be better off if both of them choose to defect simultaneously by deviating from $\{1,1\}$. If $b-c/2-\delta > 0$, we have p^*, $q^* < 0$ and $\frac{\partial \Pi_1(p)}{\partial p} < 0$ and $\frac{\partial \Pi_2(q)}{\partial q} < 0$. So, both players will be better off if both of them choose to defect simultaneously by deviating from $\{p^*, q^*\}$.

Proposition 1(6) and (7) address the boundary conditions. If $b = c$, $\{\mathit{defection}, \mathit{defection}\}$ is the Nash equilibrium. The only direction for players to deviate is to cooperate. Because $b-c/2-\delta > 0$, $\frac{\partial \Pi_2(q)}{\partial q} = -p(b-c/2-\delta) < 0$ for any $p > 0$, and thus, Player 2 will not cooperate even if Player 1 deviates to cooperate. On the other hand, if $\frac{b-c}{b-c/2-\delta} = 1$, $\frac{\partial \Pi_2(q)}{\partial q} = b-c-p(b-c/2-\delta) > 0$ for any $0 \leqslant p \leqslant 1$ as long as $b-c/2-\delta > 0$. Thus, Player 2 will not defect even if Player 1 deviates to defect. □

Proof of Proposition 2. We show that the payoff of a player in a special continuous-strategy e-collaboration game can be used to describe the payoff of the player in a discrete- and mixed-strategy e-collaboration game. From (1), we may have Player 1's payoff in a discrete-strategy e-collaboration game as following:

$$\begin{aligned}\Pi_1(p) &= pq(b-c/2) + p(1-q)(b-c) + (1-p)q(b-\delta)\\ &= p(b-c) + q(b-\delta) + pq(c/2+\delta-b).\end{aligned}$$

Let $x_m =$ and $y_m = 1$. And let $b-c/2$, $b-\delta$, and $c/2+\delta-b$ be the coefficients of the collaboration effort and the correlated item px_mqy_m, which results in Proposition 2. □

Proof of Proposition 3. Driving the first-order conditions from Eqs. (11) and (12) results in

$$\frac{\partial \Pi_1(p,q)}{\partial p} = 2(\alpha_1 - c_1)px_m^2 + (\alpha_2 - c_2)x_m + \lambda x_m q y_m$$

and

$$\frac{\partial \Pi_2(p,q)}{\partial q} = 2(\beta_1 - d_1)qy_m^2 + (\beta_2 - d_2)y_m + \lambda p x_m y_m.$$

Further, setting $\frac{\partial \Pi_1(p,q)}{\partial p} = 0$ and $\frac{\partial \Pi_2(p,q)}{\partial q} = 0$ provides solutions $\{p^*, q^*\}$ to above equations if they are the optimal points of (11) and (12). We have

$$p^* = \frac{(\alpha_2 - c_2) + \lambda q y_m}{2(c_1 - \alpha_1)x_m} \tag{A.1}$$

and

$$q^* = \frac{(\beta_2 - d_2) + \lambda p x_m}{2(d_1 - \beta_1)y_m}. \tag{A.2}$$

Now consider the concavity of (11) and (12). The strict concavity of (11) requires $\frac{\partial^2 \Pi_1(p,q)}{\partial p^2} < 0$ such that $\alpha_1 < c_1$. Similarly, the strict concavity of (12) requires $\beta_1 < d_1$.

Consider that the effort index should be between 0 and 1. Without the boundary points, suppose we have $0 \leqslant p^* \leqslant 1$ and $0 \leqslant q^* \leqslant 1$. Thus $\{p^*, q^*\}$ will be the unique equilibrium for both players when $\alpha_1 < c_1$ and $\beta_1 < d_1$. Then we replace q with Eq. (A.2) into (A.1) and obtain the following solution:

$$p^* = \frac{2(\alpha_2 - c_2) - \frac{\lambda(d_2-\beta_2)}{d_1-\beta_1}}{4(c_1 - \alpha_1) - \frac{\lambda^2}{d_1-\beta_1}} \frac{1}{x_m}$$

and

$$q^* = \frac{2(\beta_2 - d_2) - \frac{\lambda(c_2-\alpha_2)}{c_1-\alpha_1}}{4(d_1 - \beta_1) - \frac{\lambda^2}{c_1-\alpha_1}} \frac{1}{y_m}. \qquad \square$$

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