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Tripartite dynamic interactions on the scientific knowledge development of ICEV, BEV and HEV technologies

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Summary

The powertrain technologies of conventional, battery and hybrid vehicles are known by competence-sustaining, -destroying and -expanding innovations, respectively. We aim to study how they influence one another in terms of scientific knowledge growth. Using the Technological Innovation System framework and the Lotka-Volterra model, we argue that a powertrain technology with positive or negative knowledge growth can create positive or negative externalities in the others. The scientific knowledge is measured by extracting 55,529 scientific publications from Scopus over 1985-2016. Results show that they interact with one another mostly in the form of biological relationships of amensalism, commensalism, parasitism and symbiosis.

1 Introduction

The technological discontinuity of mobility electrification has opened up an 'era of ferment' wherein the alternatives of battery (BEV) and hybrid electric vehicles (HEV) are intertwined with the dominant design of internal combustion engine vehicles (ICEV), especially in terms of knowledge development [1]. The era of ferment is characterized by technological discontinuity, increased technological experimentations, high risks and uncertainty and the frequent entries and exits of companies [2]. While the dominant design of ICEV is known by competence-sustaining innovations in the industry, the alternatives of BEV and HEV are known by competence-destroying and competence-expanding innovations, respectively [3, 4]. It is, hence, critical to discover and analyse the way the knowledge dimension of the powertrain technologies is interacting and influencing in the era of ferment.

Some qualitative studies in the transition research have implied to the interactions between the powertrain technologies in terms of the knowledge development. For instance, the interaction between HEV and BEV was argued to be mutually positive as both have been taking advantage of technological advancements made in the components of one another such as batteries, electric engines, and engine control systems [5, 6]. Some quantitative studies have applied patent data analysis [7-10], citation data analysis [11], bibliometric data analysis [12], and prototype data analysis [13] to investigate their scientific and technological knowledge evolution.

The analysis of the quantitative and qualitative studies in the literature has been rather subtle to demonstrate and elaborate the positive and negative influences between the powertrain technologies in terms of scientific knowledge growth. We address this by answering our research question *'why and how the scientific knowledge growth in a powertrain technology is influenced and interacting with the scientific knowledge growth in the other powertrain technologies?'*

According to the technological innovation system (TIS) framework, technologies may influence one another vis-a-vis knowledge development co-dynamic and the interaction can be established in the form of biological relationship modes i.e. competition, symbiosis, parasitism, commensalism, amensalisn, and neutralism [2, 14, 15]. Using the TIS framework as the conceptual model and the Lotka-Volterra equations as the quantification model, we argue that a powertrain technology with positive or negative knowledge growth can create positive or negative externalities in the other powertrain technologies. The scientific knowledge is measured by extracting 55,529 scientific publications from Scopus and the data are analysed for the episodes of 1985-2006, 1997-2007, and 2008-2016. Results show that not only the scientific attractiveness and carrying capacity of the powertrain technologies change with time, but also the modes of interaction between them go through temporal transitions, mostly between commensalism, parasitism, amensalism and symbiosis.

This article is structured as follows. Section 2 presents the research background. Section 3 presents the methodology. Section 4 presents results, and Section 5 presents our discussion and conclusions.

2 Literature review

2.1 Powertrain technologies in the era of ferment

The automotive era of ferment with the technological discontinuity of the mobility electrification [16] can be characterized by an increase of technological variations and experimentations, high risk and uncertainty, and frequent entries and exits of companies [3, 16-18]. The era has been influenced by policy, economy, technologies, environment, and consumption psychology [19]. While ICEV represents as the incumbent technology (dominant design) with competence sustaining innovations [3], BEV is known as a disruptive technology with competence destroying innovations, and HEV as a bridging technology with competence expanding innovations [3]. The incumbent, bridging, and emerging technologies influence one another in an intricated and intensified interaction in order to win the selection process in the changing and uncertain environment of automotive industry [3].

2.2 Powertrain penetration models

The powertrain penetration models are categorised into agent-based studies [20, 21], consumer choice studies [22], diffusion studies [23], time series studies [8, 9], or transition studies [6, 17]. These studies have taken advantage of patent data analysis [7-10, 18, 24], citation data analysis [11], bibliometric data analysis [12], prototype data analysis [13] or a combination of the analyses [11, 13, 25] in order to analyse the convergence/divergence strategies of firms with regard to the powertrain technologies, and to compare their specialization, portfolios and responses to the governmental technology-forcing policies.

Along with the quantitative studies, few qualitative studies in the transition research have implied to interactions between the powertrain technologies in terms of the knowledge development dynamic. For instance, they argue that while HEV has been exploiting the long history of technological advancement in ICEV because it shares various components with ICEV, the interaction has hardly happened the other way around [5, 6, 17]. The interaction between HEV and BEV was argued to be mutually positive as both technologies have been using each other's technological advancement in batteries, electric engines, engine control systems etc. [5, 6]. Or ICEV has since 2000s greatly improved its fuel efficiency by adopting the electronic components of BEV [6].

Our literature review depicts that the analysis of most of the studies has been insufficient to elaborate and quantify the positive and negative influences between powertrains in the terms of scientific knowledge growth.

2.3 Interactions between powertrains

Based on the technological innovation system (TIS) framework [26], studying the interactions between the powertrain technologies requires a socio-technical system view that appreciates the scientific, technological, organizational and institutional adaptations and co-evolutions between them [14, 17]. The TIS framework takes each powertrain technology as a system with seven internal dynamics as the socio-technical dimensions of a single technological system. The seven internal dynamics[1] (i.e. knowledge development, knowledge diffusion, entrepreneurial activities, guidance of search, resource mobilization, market formation and creation of legitimacy) are known as the key (sub) processes for developing, diffusing and utilizing the system in society [26]. Taking a dynamical unit of analysis, Mirzadeh Phirouzabadi, et al. [2] have argued in their *dynapstic* framework[2] that the internal dynamics of technological systems may interact and influence each other like biological species in an ecology [14, 15], with coining the term 'co-dynamics'. They define 'co-dynamics' as those (sub-) processes and activities that crossover the boundaries of technological systems and shape couplings and overlaps between the systems with bilaterally or unilaterally positive and negative impacts [2].

Hence, technologies in general, and the powertrain technologies in particular, have the capacity to mutually or bilaterally support and inhibit the scientific knwoledge growth of one another. The six modes of interaction are described in Table 1.

Table 1: Modes of interaction between two TISs [14, 15]

Mode of interaction	Trading effects		Description
Competition	+	+	Both TISs have a negative influence on each other
Symbiosis	-	-	Both TISs have a positive influence on each other
Neutralism	0	0	Neither affects the other
Parasitism	-(+)	+(-)	One TIS has a positive influence on another, while the other TIS has a negative influence (or vice versa)
Commensalism	0(-)	-(0)	One TIS has a positive influence on another, while the other TIS has no influence (or vice versa)
Amensalism	0(+)	+(0)	One TIS has a negative influence on another, while the other TIS has no influence (or vice versa)

2.4 The L-V model

Among the numerous quantifying techniques in the literature such as Logistic, Gompertz, Sharif-Kabir, Bass, and simple exponential function [27-29], the biological equations model of Lotka-Volterra (L-V) [30, 31] have been frequently applied to formulate and quantify both the internal and external dynamics and co-dynamics of various technologies such as skyscraper and cement [29] and powertrain [1, 4]. [1] and [4], however, have investigated the various relationship modes between powertrains in terms of technological rather than knowledge growth using patents data [32]. In this article, we will investigate the various relationship modes between powertrains in terms of scientific knowledge growth using bibliometric data extracted from Scopus.

3 Methodology

3.1 The scientific knowledge indicator

The scientific knowledge state of a technology can be measured by the number of scientific publications (i.e. journal articles, books, book chapters, and conference proceedings) in the field as it can represent the scientific performance of the technology in the basic research stage of its life cycle [33]. A number of studies in the automotive industry have used the bibliometrics data to measure the scientific performance of powertrain technologies [25, 33, 34]. We preferred to not include R&D investments and spending in our

[1] Since our aim is to investigate the scientific and technological interactions between the powertrain technologies, we only investigate the knowledge development co-dynamic as unit of analysis in our study.
[2] *The dynapstic* framework in their research is short for 'a **dyn**amic **ap**proach to **s**ocio-**t**echnical **i**ntera**c**tion'.

research as car manufacturers do not usually distinguish between the allocated budget according to each technology [13].

3.2 Observation Period

The time frame of 1985-2016 are chosen as the year 1985 is known as a starting point for the sustainable development, mobility and transport discourses in the late 1980s, and the year 2016 can assure the availability of publications data. Like some recent studies [1, 4, 7, 32], the data are analysed for the three individual episodes of ‘towards sustainable mobility’ (1985-1996), ‘towards hybridisation’ (1997-2007), and ‘towards mass commercialisation’ (2008-2016) based on the industry’s major milestones.

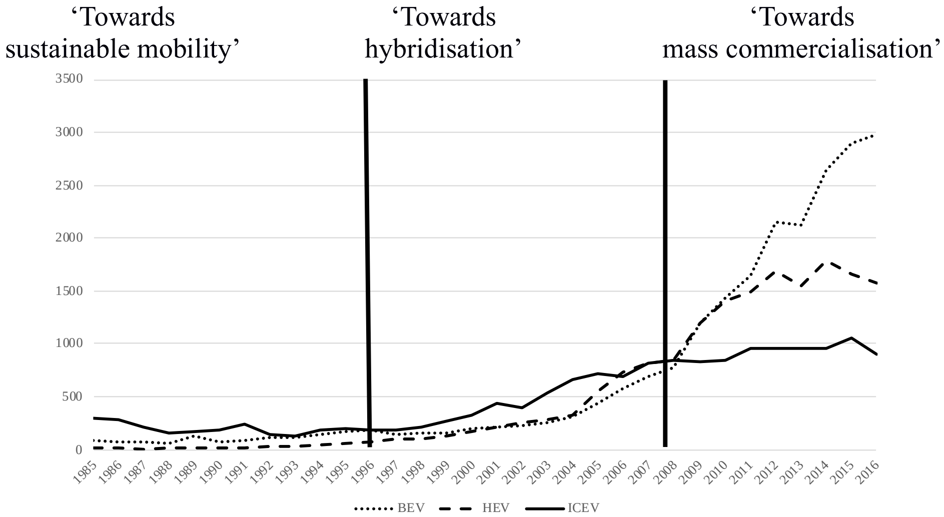
3.3 Data collection

The data collection occurred in October of 2018. We extracted the scientific publications (i.e. journal articles, books, book chapters, and conference proceedings) related to the powertrain technologies from the Elsevier’s database Scopus[3] as one of the main sources of bibliometric data. We used specified search terms in either title, abstract, or keywords of scientific contents that were published in the form of journal articles, books, book chapters, and conference proceedings for every powertrain technology (Appendix 1). In total, we received 55,529 scientific publications in the field of conventional and alternative powertrain technologies over the period of 1985-2016 (Table 1). Figure 1 demonstrates the absolute and relative number of publications for ICE, HEV, and BEV technologies over the three episodes.

Table 2: The absolute and relative number of scientific publications in the field of powertrain technologies

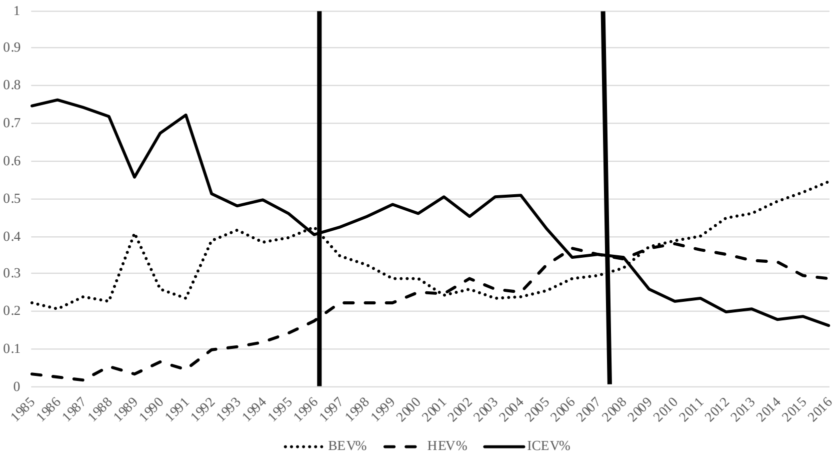
Scientific knowledge indicator		ICEV	HEV	BEV	Total
Scientific publications	Absolute	15,907	17,143	22,479	55,529
	Relative	28.65%	30.87%	40.48%	100.00%

As illustrated by Figure 1, the ICEV powertrain technology is dominant in terms of number of scientific publications up until the late 2000’s. The BEV powertrain technology gains its momentum as early as 1985, however, the number of scientific publications does not increase much until the mid-2000’s. The hybrid powertrain technology does not gain momentum until the mid 1990’s and for several years it overtakes the emerging powertrain technology. The BEV powertrain technology gains an accelerated sustained growth in the late 2000’s and becomes the dominant design after the year 2010.



(a) Absolute number

3 www.scopus.com



(b) Relative share

Figure 1: Total scientific publications (1985-2016)

3.4 The L-V equations

The L-V equations model can express the intra-population and inter-population interactions between the three powertrain technologies of ICEV, HEV, and BEV in the form of three differential equations as follows:

$$\begin{aligned}\frac{d(PUB_{ICEV,t})}{dt} &= \big(a_{ICEV} - b_{ICEV}(PUB_{ICEV,t}) - c_{ICEV,HEV}(PUB_{HEV,t}) \\ &\quad - c_{ICEV,BEV}(PUB_{BEV,t})\big)(PUB_{ICEV,t}) \\ &= a_{ICEV}(PUB_{ICEV,t}) - b_{ICEV}(PUB_{ICEV,t})^2 \\ &\quad - c_{ICEV,HEV}(PUB_{HEV,t})(PUB_{ICEV,t}) - c_{ICEV,BEV}(PUB_{BEV,t})(PUB_{ICEV,t})\end{aligned} \tag{1}$$

$$\begin{aligned}\frac{d(PUB_{HEV,t})}{dt} &= \big(a_{HEV} - b_{HEV}(PUB_{HEV,t}) - c_{HEV,ICEV}(PUB_{ICEV,t}) \\ &\quad - c_{HEV,BEV}(PUB_{BEV,t})\big)(PUB_{HEV,t}) \\ &= a_{HEV}(PUB_{HEV,t}) - b_{HEV}(PUB_{HEV,t})^2 \\ &\quad - c_{HEV,ICEV}(PUB_{ICEV,t})(PUB_{HEV,t}) - c_{HEV,BEV}(PUB_{BEV,t})(PUB_{HEV,t})\end{aligned} \tag{2}$$

$$\begin{aligned}\frac{d(PUB_{BEV,t})}{dt} &= \big(a_{BEV} - b_{BEV}(PUB_{BEV,t}) - c_{BEV,ICEV}(PUB_{ICEV,t}) \\ &\quad - c_{BEV,HEV}(PUB_{HEV,t})\big)(PUB_{BEV,t}) \\ &= a_{BEV}(PUB_{BEV,t}) - b_{BEV}(PUB_{BEV,t})^2 \\ &\quad - c_{BEV,ICEV}(PUB_{ICEV,t})(PUB_{BEV,t}) - c_{BEV,HEV}(PUB_{HEV,t})(PUB_{BEV,t})\end{aligned} \tag{3}$$

a_i and b_i are the intrinsic growth and decline rates of technology i when it is lining alone, and C_{ij} $(i \neq j)$ is the external interaction growth effect of technology j on technology i when they are living with one another. Depending the effect is positive, negative, or neutral, one of the six modes of interactions in Table 1 can be determined between technologies. When we divide a_i by b_i, we can calculate the maximum capacity that technology i can bear considering the limited resources [35]. This is called carrying capacity (k).

Since our publications database is discrete, we applied the discrete time formats of the L-V equations [36]. For the case of ICEV technology, they are as follows:

$$PUB_{ICEV,t+1} = \frac{\alpha_{ICEV}(PUB_{ICEV,t})}{1 + \beta_{ICEV}(PUB_{ICEV,t}) + \gamma_{ICEV,HEV}(PUB_{HEV,t}) + \gamma_{ICEV,BEV}(PUB_{BEV,t})} \tag{4}$$

Here, α_i corresponds to a_i, β_i to b_i, and γ_{ij} to c_{ij}. They can be calculated through one another as follows [36]:

$$a_{ICEV} = \ln \alpha_{ICEV} \tag{5}$$

$$b_{ICEV} = \frac{\beta_{ICEV} \ln \alpha_{ICEV}}{\alpha_{ICEV} - 1} \quad (6)$$

$$c_{ICEV,HEV} = \frac{\gamma_{ICEV,HEV} \ln \alpha_{ICEV}}{\alpha_{ICEV} - 1} \quad (7)$$

3.5 Method

To estimate the three parameters mentioned above, we used Statistical Package for Social Sciences (SPSS) and Microsoft Excel. The non-linear least-square method was chosen to estimate the parameters. We adopted the Levenberg-Marquardt algorithm as iterative procedure to set the iteration limits and convergent standards. We set the iteration convergence criterion at 0.0001, so the iteration would halt when the maximum variance of the parameters was less than 0.0001 [37]. The initial value of α_i was set at 1 and the rest of parameters as β_i and γ_{ij} started from 0.001.

4 Results

Our estimation results for the first episode in Table 3 indicate that BEV is the only powertrain technology with positive intrinsic scientific knowledge growth rate (a=2.23E-01) as the intrinsic scientific knowledge growth rate of both ICEV and HEV is estimated to be negative (a=-5.04E-02 and a=-1.04E-01, respectively). Additionally, we found BEV as the powertrain with largest carrying capacity for developing scientific knowledge (k=6.50E+01) in the industry. Thus, in the first episode, BEV is found as the only powertrain technology that is not only attractive to the scientific society, but also is able to capacitate annually 65 scientific publications. Our estimation results for the inter-powertrain relationships (Table 4) indicate that HEV benefits from the scientific knowledge growth of BEV in a commensal relationship mode (C=0 and C=-6.39E-03) while BEV itself benefits from the scientific knowledge growth of ICEV through the same relationship mode (C=0 and C=3.79E-03). On the contrary, we found a negative interaction between ICEV and HEV as the scientific knowledge growth of ICEV is estimated to be inhibited by HEV vis-à-vis an amensalism relationship mode (C=0 and C=7.10E-04).

Not only does the intrinsic scientific knowledge growth rate of all the three powertrain technologies increase in the second episode, but also does their carrying capacity experience a considerable increase. With all these increases, BEV still remains both as the most attractive powertrain technology to the scientific community (a=4.90E-01) and the powertrain technology with the largest scientific carrying capacity in the industry (k=3.94E+02). The incumbent ICEV is estimated to be the least attractive powertrain technology with the smallest scientific carrying capacity in the industry (a=8.52E-02 and k=6.43E+01). According to the estimated interactions, BEV starts benefitting from the scientific knowledge growth of both HEV and ICEV vis-à-vis parasitic (C=-5.62E-04 and C=3.56E-03) and symbiotic relationships (C=-4.85E-03 and C=-5.74E-04), respectively. HEV also starts enjoying the scientific knowledge growth of ICEV through a commensalism mode (C=0 and C=-9.36E-04).

The incumbent ICEV loses its scientific attractiveness in the third episode as we found the estimated intrinsic growth rate of the powertrain not statistically significant. Like in the previous two episodes, we found BEV as the most attractive powertrain technology to the scientific community (a=6.93E-01) and as the powertrain technology with the largest scientific carrying capacity in the industry (k=4.97E+03). It's noticeable that the BEV scientific carrying capacity has increased remarkably in the third episode. The hybrid powertrain technology is estimated as the second most attractive option (a=2.55E-01) and as the second largest scientific carrying capacity (=6.47E+02). The only meaningful, significant relationship as shown in Table 4 is the commensal relationship between HEV and ICEV, within which HEV is enjoying the scientific growth rate of ICEV (C=0 and C=-6.07E-04), like in the second episode.

Table 3: The parameter estimation results for scientific publications

	Parameters (t–value)						
	a_i	b_i	k_i=a_i/|b_i|	$C_{i,ICEV}$	$C_{i,HEV}$	$C_{i,BEV}$	R2
	Towards sustainable mobility (1985–1996)						
ICEV	-5.04E-02	1.44E-03	-3.51E+01	-	4.75E-03	-3.79E-03	0.627
	(2.03E+00***)	(6.76E-01*)		-	(7.64E-01)	(-1.24E+00*)	
HEV	-1.04E-01	1.01E-02	-1.03E+01	7.10E-04	-	-6.39E-03	0.965
	(2.56E+00***)	(2.38E+00***)		(4.10E-01***)	-	(-2.36E+00***)	
BEV	2.23E-01	3.43E-03	6.50E+01	-9.88E-04	-5.30E-03	-	0.655
	(1.43E+00***)	(3.60E-01*)		(-5.99E-01)	(-3.51E-01)	-	
	Towards hybridisation (1997–2007)						
ICEV	8.52E-02	1.33E-03	6.43E+01	-	2.65E-03	-4.85E-03	0.888
	(2.81E+00***)	(1.03E+00*)		-	(1.20E+00)	(-1.68E+00*)	
HEV	2.23E-01	-1.79E-03	1.25E+02	-9.36E-04	-	3.56E-03	0.976
	(4.57E+00***)	(-1.42E+00*)		(-3.25E+00***)	-	(2.00E+00*)	
BEV	4.90E-01	1.24E-03	3.94E+02	-5.74E-04	-5.62E-04	-	0.994
	(2.13E+01***)	(2.60E+00***)		(-5.56E+00***)	(-1.59E+00*)	-	
	Towards mass commercialisation (2008–2016)						
ICEV	1.09E+01	1.63E-02	6.64E+02	-	-1.70E-03	-1.09E-03	0.716
	(5.19E-05)	(5.19E-05*)		-	(-5.19E-05)	(-5.19E-05)	
HEV	2.55E-01	3.94E-04	6.47E+02	-6.07E-04	-	4.69E-05	0.681
	(2.17E+00***)	(1.38E+00*)		(-1.92E+00**)	-	6.99E-01	
BEV	6.93E-01	-1.40E-04	4.97E+03	-2.20E-04	6.81E-04	-	0.924
	(1.06E+00*)	(-7.25E-01*)		(-3.17E-01)	(8.27E-01)	-	
	The entire period (1985–2016)						
ICEV	2.24E-01	7.66E-04	2.92E+02	-	-4.10E-04	3.59E-05	0.936
	(6.09E+00***)	(1.66E+00*)		-	(-1.70E+00*)	(4.68E-01)	
HEV	1.22E-01	2.49E-04	4.88E+02	-4.13E-04	-	4.37E-05	0.987
	(6.10E+00***)	(2.40E+00***)		(-2.07E+00***)	-	(1.08E+00)	
BEV	4.79E-01	9.90E-05	4.84E+03	-2.37E-04	2.13E-04	-	0.978
	(4.79E+00***)	(1.69E+00***)		(-8.40E-01***)	(1.34E+00***)	-	

Notes: *,**,*** significant at p<0.1; p<0.05; p<0.01

The scientific knowledge estimation results for the entire period indicate that overall the emerging powertrain technology of BEV is recognised as the dominant design both in terms of scientific knowledge attractiveness and scientific carrying capacity (a=4.79E-01 and k=4.84E+03). While ICEV is estimated to be the second most attractive powertrain with a=2.24E-01, HEV is estimated to possess the second largest carrying capacity for scientific knowledge after BEV with k=4.88E+02. The scientific knowledge interaction results for the entire period in Table 4 indicate that BEV is inhibiting the scientific knowledge growth of HEV via an amensalism mode of interaction (C=0 and C=2.13E-04) and ICEV is benefitting from the scientific knowledge growth of BEV and HEV via commensalism (C=0 and C=-2.37E-04) and symbiosis (C=-4.13E-04 and C=-4.10E-04), respectively.

Table 4: Dynamic interactions between scientific publications

Technologies		'Towards sustainable mobility' (1985-1996)		'Towards hybridisation' (1997-2007)		'Towards mass commercialisation' (2008-2016)		The entire period (1985–2016)	
i	j	$C_{i,j}$	$C_{j,i}$	$C_{i,j}$	$C_{j,i}$	$C_{i,j}$	$C_{j,i}$	$C_{i,j}$	$C_{j,i}$
BEV	HEV	0	-6.39E-03	-5.62E-04	3.56E-03	0	0	2.13E-04	0
		commensalism		predator-prey		Neutralism		amensalism	
BEV	ICEV	-3.79E-03	0	-4.85E-03	-5.74E-04	0	0	0	-2.37E-04
		commensalism		symbiosis		Neutralism		commensalism	
HEV	ICEV	7.10E-04	0	-9.36E-04	0	-6.07E-04	0	-4.13E-04	-4.10E-04
		amensalism		commensalism		commensalism		symbiosis	

Notes: The values of those coefficients that were found statistically insignificant were set to zero.

5 Discussion and conclusions

The intrinsic scientific knowledge growth of a technology may affect other technologies' scientific knowledge growth rates [1]. A technology with a positive or negative intrinsic scientific growth may create either positive or negative scientific knowledge externalities, or both, in other technologies. The externalities are known as the 'mirror effects' of the positive or negative intrinsic growth [38]. Mirzadeh Phirouzabadi, et al. [2] argue that the positive and negative externalities are being carried through the 'knowledge development co-dynamics', i.e. the (sub-) processes and activities coupled between two TISs. Such co-dynamics can initiate scientific or technological spillovers between TISs, which can lead to scientific or technological knowledge 'overlaps' or 'couplings' between them. This is supported by the fact that the knowledge domain of one TIS is driven by a recombinant of the knowledge domains of other TISs [1]. The spillovers can occur "… within the same specific technological field (intra-technology spillovers), to other technologies in the field … (inter-technology spillovers), and to technologies unrelated … (external-technology spillovers)" [39: p. 1].

The direction of spillovers depends on whether a TIS chooses to behave as knowledge explorer (innovator) or knowledge exploiter (imitator), or both [1, 2, 40]. In case of acquiring new knowledge by the TIS during an interaction with other TISs, the interaction will direct the spillovers towards the TIS. If the TIS loses knowledge during the interaction, the relationship will direct the spillovers from the TIS to the other TISs. For example, in the scientific predator-prey relationship of BEV with HEV we can observe that the explorer powertrain technology of HEV was the prey of the less explorer and more exploiter powertrain technology of BEV in the second episode. Two TISs of the same nature, either explorative or exploitative, may potentially create a competitive (mutually inhibitive) situation since they look for the same knowledge or source of ideas [2].

While we did not observe any pure competitive relationships, we found some sort of semi-competitive relationships between them. For example, we found a negative interaction between ICEV and HEV in the first episode as the scientific knowledge growth of ICEV was estimated to be inhibited by HEV vis-à-vis an amensalism relationship mode. Additionally, the scientific knowledge interaction results for the entire period indicated that BEV was inhibiting the scientific knowledge growth of HEV via an amensalism mode. We additionally observed that the behaviour of powertrain technologies changes throughout time as the relationship between them changes. For instance, the relationship between BEV and HEV started with commensalism, continued with parasitism and ended with neutralism. When the powertrain technologies go through the temporal shiftings phenomenon, they may switch from exploration to exploitation, or vice versa. Hence, a generic or specific periodic combination or spiral of exploration, exploration-to-exploitation, exploitation, and exploitation-to-exploration may build up between them over time [1, 2, 4, 40]. This situation is more frequent for a technology that is a recombinant of other technologies e.g. HEV. Though a 'creative accumulation' process, HEV starts searching and acquiring new complementary knowledge from BEV, and then exploits and integrates them with the existing knowledge rather than replacing them [3]. Future studies, however, may look into the detailed reasons behind the temporal shiftings and change of behaviour of the powertrain technologies with further excavations into the endogenous and exogenous factors.

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Appendix

Search terms for the Elsevier's Scopus database

Scientific field	Search query
ICEV-related publications	TITLE-ABS-KEY (("internal combustion engine*") OR "IC engine*" OR "diesel engine*" AND (vehicle* OR car OR automobile*))
HEV-related publications	TITLE-ABS-KEY (hybrid W/1 (vehicle* OR automobile* OR car))
BEV-related publications	TITLE-ABS-KEY ((vehicle* OR automobile* OR car) AND (electric AND batter*))

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