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ARE BIG DATA A RADICAL INNOVATION TRIGGER OR A PROBLEM-SOLVING PATCH? THE CASE OF AI IMPLEMENTATION BY AUTOMOTIVE INCUMBENTS

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ABSTRACT: Big data, supported by AI technologies, is mainly viewed as a trigger for radical innovation. The automotive industry appears as a key example: the most critical innovative challenges (e.g., autonomous driving, connected cars) imply drawing more extensively on big data. But the degree of innovativeness of the industrial purpose of incumbents, who are already embedding such technologies in their end-products, is worth investigating. To answer this research question, we relied on a mixed-method approach and used knowledge search as a theoretical framework. First, we conducted a quantitative analysis on 46,145 patents from the top-19 automotive incumbents. By comparing AI and non-AI patents, we showed that incumbents mainly rely on knowledge exploitation for data-driven innovation leading to incremental innovations. But, surprisingly, such innovation path foster more technologically original inventions with AI, which is not the case for non-AI patents. Second, we conducted a qualitative study to better understand this phenomenon. We showed that big data and AI technologies are integrated in the industrialization phase of new vehicles development process, following creative problem-solving logics. We also retrieved technical and organizational challenges limiting data-driven innovation. Those findings are discussed regarding the knowledge search and the new product development literature in the context of automotive industry.

KEYWORDS: Big data, AI technologies, automotive industry, digital transformation

ARE BIG DATA A RADICAL INNOVATION TRIGGER OR A PROBLEM-SOLVING PATCH? THE CASE OF AI IMPLEMENTATION BY AUTOMOTIVE INCUMBENTS

1. INTRODUCTION

Digital transformation has a considerable impact on multiple dimensions of companies' innovation processes (see Appio et al., 2021 for a review). The rise of the data economy allows companies to collect, store and exploit more and more data points, which are exploited through advanced techniques, such as Artificial Intelligence (IA).

The 180-years old automotive industry faces major changes along with this digital transformation (Bohnsack and Pinkse, 2017; Skeete, 2018; Wells et al., 2020). All of the critical innovation challenges in this industry—autonomous driving, connected cars, powertrain electrification, and shared mobility—imply more significant and broader data collections and advanced exploitation of those data (Hofmann et al., 2019; Mohr et al., 2016). It is worth noticing that new external actors with vast experience in the digital field are entering this industry, such as Tesla, Google, or Uber (Liu and Liu, 2018). In this paper, we propose to investigate how incumbents, both traditional car manufacturers and Original Equipment Manufacturers (OEMs), can face this competitive threat by developing innovative products that integrate big data and associated AI techniques.

The automotive industry has based its longstanding success on an established New Product Development (NPD) process in which engineers tap in a stock of incrementally renewed expertise, and through the development of *Innovative Features* developed by Advanced Engineering Teams (Maniak et al., 2014). In order to pursue more explorative projects, automotive companies relied on dedicated ad hoc organizations following an ambidextrous approach (e.g., Lo and Fatien-Diochon, 2020; Lo and Theodoraki, 2021). But this dual organization between knowledge exploitation on one side, and exploration on the other, may appear limited to foster innovation as big data and AI constitutes a new technology with the potential to affect all sort of vehicles new projects, Innovative Features and the NPD process itself. Hence, further investigations are needed to better understand how incumbents cope with such new technologies, and to what extent they rely on their traditional ambidextrous approach to do so. **Hence, the question of *how* automotive industry incumbents innovate by integrating big data and AI technologies in their products, i.e., what is their industrial purpose when relying on such breakthrough technologies, is worth investigating**.

Our research question drew on the knowledge search perspective (e.g., Fleming, 2001). This literature notably built on the March (1991) dilemma to better understand how inventors or companies manage to either exploit their existing knowledge or explore new paths in combining knowledge leading to radical innovation (Arts and Fleming, 2018; Arts and Veugelers, 2015). Indeed, theoretical constructs and methodologies developed in this literature stream help to identify and analyse different *knowledge search practices* that automotive companies could rely on for their innovation process (Kneeland et al., 2020; Yayavaram and Chen, 2015). Those practices will imply different degree of explorativeness or exploitativeness in companies' innovation processes, in relation to their expertise and mastered knowledge conceptualized as *companies' knowledge bases* (e.g., Grant, 1996; Yayavaram and Ahuja, 2008).

To investigate how automotive incumbent companies capitalize on big data—exploited through AI technologies—to explore new innovative paths, we used a mixed-method approach. First, we relied on a quantitative analysis by reviewing 44,668 patent families filed by 19 innovative companies in this sector (car manufacturers and OEMs). We clustered the retrieved inventions between AI-based, non-AI-based and electric propulsion and battery (i.e., called EV propulsion) and we compared each category according to their *knowledge search modes* related to different degrees of explorativeness or exploitativeness (Plantec et al., 2021), and technological originality (Alstott et al., 2017a, 2017b; Plantec et al., 2021). Second, we conducted a qualitative analysis to gain more fine-grained data on the NPD process by conducting ten semi-structured interviews with inventors of AI-based patents retrieved in our quantitative analysis. By comparing AI and non-AI patents, we showed that incumbents mainly rely on knowledge exploitation for data-driven innovation leading to incremental innovations. But surprisingly, such innovation path foster more technologically original inventions with AI, which is not the case for non-AI patents. We demonstrate that big data and AI technologies are integrated in the industrialization phase of new vehicles development processes, following creative problem-solving logics. We also identified technical and organizational challenges limiting data-driven innovation. Those findings are discussed regarding the knowledge search and the new product development literature in the context of the automotive industry.

2. LITTERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Big data and AI technologies for innovation in the automotive industry

While *big data* definition is not consensual (Ekbia et al., 2015), Gandomi and Haider (2015) showed that the term is either employed to deal with the massive growth of transaction data, to describe the new technologies designated to address the challenge of managing a large amount of data, to deal with the storage and achievement requirements of data for compliance purposes, or as an explosion of new sources of data[1]. Kersting and Meyer (2018) and O 'Leary (2013) show that to derive higher value from big data, more advanced techniques such as those emerging from AI technologies are required.

[1] Adopting a more global perspective of big data, De Mauro et al. (2016) propose that it covers the three following aspects: (1) high Volume, Velocity, and Variety, to describe the characteristics of information; (2) specific Technology and Analytical Methods, to describe the requirements needed to make proper use of such information; and (3) the transformation of data into value encompassing changing information into insights that create economic value for companies and society.

AI can be defined as a discipline of computer sciences that study and design computer systems with some forms of "intelligence" such as learning new tasks and concepts or understanding languages or actions in a visual scene (Russell et al., 2010)[2].

In this study, **we intend to understand better what types of new innovative products companies develop by drawing on big data (based on AI technologies), and in particular the role of such technologies in the development of innovation**. Indeed, little is known about how companies integrate AI technologies in end-products (Smith and Beretta, 2021). **A straightforward assumption is that, due to the radicalness of those technologies, it will necessarily conduct companies to intensively explore new knowledge to conduct to radical innovation (Agrawal et al., 2017; Iansiti and Lakhani, 2020).** But, this question is worth investigating when considering the costs of big data implementation (Ceipek et al., 2021a, 2021b; Côrte-Real et al., 2017), and in particular in the case of the automotive industry.

When analyzing critical drivers of innovation in the automotive industry, it is worth noticing that big data appear crucial. One of the main challenges for the automotive companies for the next decades encompass intelligent connected cars, shared mobility, powertrain electrification, and autonomous driving: four trends that require extensive usage of data (e.g., Hofmann et al., 2019; Liu and Liu, 2018; Skouras et al., 2019). For example, electric vehicles need to be part of smart electric grids, so vehicle to grid communications with fifth-generation mobile wireless networks optimize the transmission and reception of data to improve the user experiences (Luckow et al., 2015; Skouras et al., 2019). Autonomous vehicles (AVs) are also playing a crucial role in the innovation path of this industry. In particular, the development of Advanced Driver Assistance Systems (ADAS) helps to pave the way for full autonomation (Level 5) by addressing the primary technological challenges of autonomous driving (Skeete,

[2] AI was first designated in the work of Alan Turing, "Computing Machinery and Intelligence" (Turing, 1950).

2018). The added value would be tremendous by allowing passengers and drivers to work, use social media, or rest while driving (Mohr et al., 2016).

To cope with those challenges, incumbents from the automotive industry predominantly invest in new digital technologies. Vehicles are now equipped with many sensors that acquire a large amount of data to push the industry towards the highest level of autonomous driving (Skeete, 2018). Indeed, incumbents critically need to cope with the data challenges to avoid the threat from the Internet auto companies such as Google, Tesla, Uber, and Baidu (Liu and Liu, 2018). But beyond investing in AI technologies and acquiring a large amount of data, innovation in the automotive industry largely relies on New Product Development (NPD) processes with extremely short lead time, very stable routines, and stabilized design rules (Maniak et al., 2014). Then, it may be difficult for incumbents of this industry to integrate those technologies in end-product because they can have critical impact the whole architecture of the vehicle (Henderson and Clark, 1990). The difficulties of transferring the advances made by the exploratory teams into end-products, or even as invention per se, appear critical in the automotive industry, even in the case of the development of *Innovative Features* (Maniak et al., 2014). It can be the case for big data and AI technologies, as it would require significant investments from incumbents, with no immediate pay-off and uncertain return on investment.

2.2. Knowledge search practices for big data innovation in the automotive industry

Innovation can be conceived as combining knowledge components existing in a landscape of potential opportunities, where innovators *search* (e.g., Fleming and Sorenson, 2004). We consider that drawing the knowledge search literature can support the formulation of hypotheses regarding the mechanisms by which the integration of AI technologies by the automotive industry's incumbents supports **radical invention, defined here as "*something***

***novel, that it has distinctive features missing in previously observed inventions*" (Dahlin and Behrens, 2005, p. 724)**.

2.2.1. AI technologies as a support for radical invention

From a theoretical perspective, to support radical inventions, companies need to access new knowledge components (Henderson and Clark, 1990; Katila and Ahuja, 2002; O'Connor, 2008) such as scientific knowledge (Fleming and Sorenson, 2004; Veugelers and Wang, 2019) or knowledge from different industries or other technological domains (Dahlin and Behrens, 2005; Dosi, 1982; Katila and Ahuja, 2002; Nooteboom et al., 2007). Recent advances in how we can model inventor or companies' knowledge bases as a network of knowledge components (e.g., Kneeland et al., 2020; Plantec et al., 2021; Yayavaram and Ahuja, 2008; Yayavaram and Chen, 2015) help to better understand this phenomenon by detailing what sort of combinations of knowledge can foster radical invention. Kneeland et al. (2020) proposed an integrative approach. By relying on a patent dataset, they developed a typology of three categories of knowledge search paths that can be drivers for radical inventions: long search paths (i.e.; atypical search on a known technology with multiple improvements), scientific reasoning (i.e., the using of generalized theory) and distant recombination (i.e., unusual fusion of technology domains).

In the case of the automotive industry, following Kneeland et al. (2020) perspective, we could claim that **many advances in sub-AI technologies field such as deep learning, environment analysis, and decision management might be combined with previous automotive technologies such as ADAS systems, creating *distant recombination* or fostering *long search paths* to explore uncharted territories**. Moreover, as AI technologies are still close from fundamental research, it creates opportunities for new product development based on *scientific reasoning*. Many companies, including GAFAM, had to engage in significant fundamental corporate science development to develop AI technologies, notably to exploit their owned data (Hartmann and Henkel, 2020). For example, in the automotive industry, Renault, Audi, Volkswagen, Ford, and General Motors have published 117 scientific papers on AI technologies since 2000[3].

In the knowledge search perspective, such creation of novel distant combination of knowledge is the main driver of technological originality (e.g., Henderson and Clark, 1990; Schumpeter, 1934; Teece, 1996). For example, Verhoeven et al. (2016) showed that inventions which combine both recombination of knowledge with either novel technological knowledge or scientific knowledge, have a greater *impact* than any other patents. To measure impact, they relied on patent citations, a usual proxy for technological originality or value of inventions. Plantec et al. (2021) showed that in the case of the oil & industry, inventions that combine two knowledge components that were distant in a given company's knowledge base, potentially also with new external knowledge, derived more technological originality than those who only drew on new-to-company knowledge or more exploitative approaches. Those conceptual elements support a similar logic in the case of AI integration in the automotive industry. Indeed, considering the complex architectural nature of the vehicles (Hargadon and Sutton, 1997), we posit that automotive companies can derive higher originality for inventions that integrated AI through greater knowledge exploration strategies.

Finally, based on the knowledge search literature, we can derive the following hypotheses:

H1. In the automotive industry, the implementation of AI-based technologies for NPD leads companies to access new knowledge extensively and create novel distant combinations of knowledge.

H2. In the automotive industry, companies derive higher technological originality from NPD projects based on AI when they access new knowledge and/or create novel combinations of knowledge.

[3] Research on Lens.org on 25/11/2021

Nevertheless, while those hypotheses seem to reflect the dominant view of AI integration in any technological sector, specifics of the automotive industry sector or big data conduct to challenge this set of hypotheses.

2.2.2. Challenge of the hypotheses

First, Yayavaram and Ahuja (2008) showed that even when facing a similar technological environment, incumbents have different knowledge base structures due to imprinting effects of past coupling decisions. Then, facing a technological change such as the emergence of big data, some companies may face difficulties in integrating the new knowledge due to a lack of *malleability* of their knowledge base, conducting to different exploration or explorative paths. In other words, due to interdependencies related to the architecture of a given product, some companies may choose to progressively absorb external local to proceed to short local moves instead of reorganizing their knowledge clusters by creating distant and highly original combinations of knowledge.

Second, the literature on big data, as well as the broader literature on digital innovations, demonstrate that integration of such technologies for radical innovation depends of companies resources, technologies, market readiness, and the willingness of the management teams to pursue such paths (e.g., Ceipek et al., 2021a, 2021b; Sun et al., 2020). Therefore, the costs of the development of big data and AI technologies can outweigh the benefits. For example, Cappa et al. (2021) showed that costs and risks associated with collecting, storing, and using big data could be detrimental to companies' performances: to derive value from big data, companies need to ensure a high quantity of various big data points and possess sufficient skills to derive relevant information for customers (Geroge et al., 2014). In the case of the automotive sector, while vehicles are equipped with more and more sensors, it is possible that the variety of data does not mean they could be managed in creative ways to derive innovation. When studying the electric vehicles market, Bohnsack and Pinkse (2017) showed that very few companies capitalize on data from other sources such as wind speed, height changes, weather conditions, or charging stations locations to develop new assistance tools.

Finally, some specifics in the innovation process of the automotive industry may reduce the ambition of incumbents to develop highly radical paths through the integration of AI technologies. The innovation process in the automotive industry is based on very short development cycles that require standardization (Cusumano & Nobeoeka, 1998) and a template logic that reproduces the global architecture of a car (Leonard-Barton, 1992). Then, disruption which impacts the global product architecture may face implementation difficulties. For example, Bohnsack and Pinkse (2017) recognized that incumbents face problems in proposing innovative paths that would be radically different from those developed for cars with an internal combustion engine (ICE) due to the amount of needed re-engineering throughout the whole industrial process. Facing these lock-in situations, automotive companies have been very creative in organizing their innovation processes to favor an ambidextrous approach (O'Reilly and Tushman, 2004). They can be based on having *Advanced Engineering Units* (AEU), which are in charge of the upstream exploration of new features that can be applied to multiple models (Maniak et al., 2014). But despite such organizational designs, "*carmakers have tried not to pollute the efficiency of their NPD process or vehicle engineering departments*" (Maniak et al., 2014, p. 122), despite that the development of new features requires continuous interactions with the development teams and a large body of knowledge is created in the development phase (Maniak et al., 2014). Therefore, in the case of radical technologies such as AI, the realization of a more explorative path might depend on the level of value management and coordination between the AEU and development teams (Gillier et al., 2015).

3. METHODOLOGY: A MIXED-METHOD APPROACH

3.1. Quantitative approach: a patent-based analysis of knowledge search practices

3.1.1. Clustering of patent data for automotive industry's incumbents

First, we collected patent data of automotive industry's incumbents. To do so, we selected major incumbents involved in innovation activities in this industry, here all companies present in ranking Top 100 Innovative Companies from Clarivate[4] in the automotive industry section, between 2012 and 2021 (e.g., Honda, Ford, GM, Renault or Toyota). Then, we collected patent data for those companies on the privately-owned DERWENT database. Some companies can have diverse activities beyond the automotive industry. Then, we selected patents classified throughout the International Patent Classification (WIPO, 2019b) in the B60 class only, which covers inventions related to vehicles in the transporting category. To ensure that we would model incumbents' knowledge base appropriately, we collected patents on a large time frame, between 1990 and 2020[5].

Second, we identify automotive patents capitalizing on AI technologies. To do so, we used an externally validated query made available by the WIPO (2019a) to retrieve AI-related patents. The query, made by a team of AI and patent retrieval experts from diverse sectors, is comprising specialized classes codes, keywords, and combinations of specialized classes and keywords. Still drawing on technological classes, we used the class B60L to retrieve electric propulsion and battery inventions.

3.1.2. From exploration to exploitation: defining knowledge search practices

In order to define the degree of explorativeness or exploitativeness of each invention, we attempt to cluster those patents according to different knowledge search practices.

[4] https://clarivate.com/top-100-innovators/the-top-100/

[5] We used patent families, instead of patent applications, as it constitutes a better descriptor of inventive activity (Martínez, 2011)

To do, company's knowledge bases are modelled in accordance with the work of Yayavaram and Ahuja (2008) and Yayavaram and Chen (2015), capitalizing on network theory. For a given invention i, there is a graph $G(i)$ comprising the vertex $V(i)$ representing the knowledge components that have to be mobilized to design the invention, and the edges $E(i)$ representing the combinations of components (ie. the structure of knowledge). The knowledge base for a given year is then the combinations of graphs of all the past inventions of the company. In our case, each vertex represents technological classes, and inventions are based on patent families[6].

The components and the structure of each invention in year *t* (i.e., the graph) are then compared with the company's knowledge base at time $t-1$, to classify inventions into different knowledge search strategies. As the distance between knowledge component in the knowledge base appear critical to understand design behaviors we rely on Plantec et al. (2021) classification of knowledge search strategies to take into account this element. Hence, four knowledge search strategies can be identified: *refinement mode* (very exploitative), *clustering mo*de (exploitative), *absorption mode* (explorative), and *recomposition mode* (very explorative). A synthetic view of those four knowledge search modes is proposed in **Table 1**, including examples and formal graph properties.

Finally, the procedure is applied to all the patent families in our dataset and we specifically analysis period 2005-2020. This period comprises 34,315 patents classified into the four knowledge search modes: 1,313 AI-based patent families, and 33,002 non-AI-based patents families for which 5,282 are patent families for electric batteries[7].

[6] To take into account knowledge cycles, we also consider that a knowledge component (ie., a vertex) is discarded if there has not been any patent filled by the company in this specific class in the six previous years and new knowledge components are considered during a 3-year period (in accordance with Plantec et al., 2021).

[7] Due to co-patenting behaviors, it leads to 36,150 company - patent observations, including 1,379 AI-based, 34,726 non-AI and 5,480 electrical battery patent families.

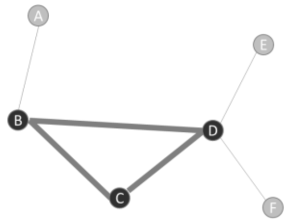
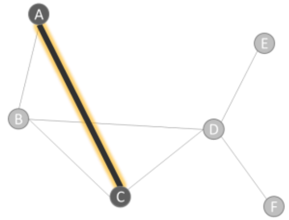
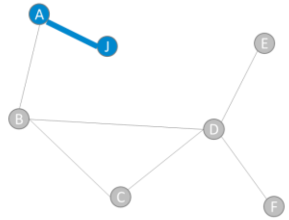
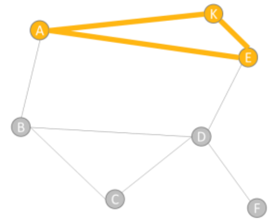
	Initialization	Refinement mode	Clustering mode	Absorption mode	Recomposition mode
Invention	*NA*	$I_{t+1} = \{1, \dots, n\}$	$I_{t+1} = \{1, \dots, n\}$	$I_{t+1} = \{[1, \dots, m], [n, \dots, o]\}$	$I_{t+1} = \{1, \dots, n\}$
Period	t	$t+1$	$t+1$	$t+1$	$t+1$
Vertex properties	NA	$V(G_{t+1}) - V(G_t) = 0$	$V(G_{t+1}) - V(G_t) = 0$	$V(G_{t+1}) - V(G_t) \geq 1$	$V(G_{t+1}) - V(G_t) \geq 0$
Edge properties	NA	$E(G_{t+1}) - E(G_t) = 0$	$E(G_{t+1}) - E(G_t) \geq 1$	$E(G_{t+1}) - E(G_t) \geq 1$	$(G_{t+1}) - E(G_t) \geq 1$
Geodesic distance properties	NA	$\max(d_t^{i-j}) = 1, \forall\, i,j \in [1,n]$	$d_t^{i-j} = 2, \exists\, i,j \in [1,n]$ $\max(d_t^{k-l}) \leq 2, \forall\, k,l \in [1,n]$	Case 1: $V(I_{t+1}) \cap V(G_t) = \emptyset$ Case 2: $d_t^{i-j} \begin{cases} = \emptyset, \exists\, i,j \in [1, \dots m] \\ \leq 2, \forall\, i,j \in [n, \dots, o] \end{cases}$	$d_t^{i-j} \in [3; +\infty[$ $\exists\, i,j \in [1,n]$
Stylized example		 $I_t = \{B, C, D\}$	 $I_t = \{A, C\}$	 $I_t = \{A, J\}$	 $I_t = \{A, K, E\}$

Table 1 - Knowledge search modes taxonomy

3.1.3. Technological originality measure

As the measure of the degree of explorativeness or exploitativeness is company-centric, one key element to evaluate the innovation performances is to measure the technological originality of each invention from a global technology landscape perspective. This measure helps to evaluate the performances of each knowledge search mode.

Considering the whole technological landscape, some knowledge components are frequently combined by inventors, while others are rarely used together to design a given invention. Hence, Alstott et al. (2017a, 2017b) used 3.9 million patents to create a technology network. Then, based on multiple measures they proposed an indicator of technological proximity between any existing pairwise of IPC4, clustered between 0 and 1. As the technology network is stable over time (Alstott et al., 2017a), evaluating technological originality can then be based on measuring the distance between knowledge components used in a given invention. The most distant the knowledge components combined in a given invention are throughout the global technological landscape, the most technologically original the invention is (Plantec et al., 2021). Formally, for each pairwise of technological classes i and j, and considering Alstott Score as the proximity measured made by Alstott & al., our originality measure (ADOI) is then $ADOI^{i-j} = 1 - Alstott\ Score^{i-j}$.

For this analysis, 21,561 patent families remain in the period 2005-2020, which is considered a sufficient threshold for our research.[8]

3.2. Qualitative analysis:

The quantitative analysis conducts us to look for more fined-grained insights regarding the NPD process related to AI-based inventions.

[8] One limitation of this indicator is that it can be computed on patent families classified in more than one technological class. Nevertheless, focusing only on multi-classes patent families is classic in the scientometric literature (e.g., Strumsky and Lobo, 2015; Verhoeven et al., 2016).

We capitalize on our qualitative analysis to select a relevant case for our qualitative research. One incumbent, Renault, was selected[9]. We extracted all patent family data from 2005 to 2020 that Renault filled in Europe (due to field access constraints [10]) and end it up with 29 patent families. Informants were contacted by e-mail[11]. Interviews took the form of guided conversation (Yin, 2003) and followed a semi-structured interview protocol.

10 interviews were performed with inventors based both in France and Spain covering 22 patent families (i.e., 75% of the retrieved patents) and covering the entire time period[12]. Interview guides were designed to better understand the context of each project that led to specific AI-based patent families. We analysed the transcripts in an inductive way by following an open-coding strategy. Interviews' details are presented in the **Table 2.**

Interview	Expertise role	Duration	Location	AI-based patents	Application Year	Theme of AI-based patents
1	Expert	53 min	France	2	2020	ADAS for parking assistance
2	Expert	1h02	France	2	2019	Lateral positioning of autonomous vehicle
3	-	1h11	France	1	2014	Autonomous vehicle speed adaptation
4	-	31 min	France	5	2015, 2017, 2018	Lateral positioning of autonomous vehicle
5	Expert	1h07	France	1	2012	Human Machine Interface for Adaptative Cruse Control
6	Expert leader	49 min	Spain	4	2019, 2020	Autonomous driving during turn
7	Expert	48 min	France	1	2020	ADAS for braking system
8	-	50 min	France	3	2013, 2021	ADAS for Adaptative Cruse Control (ACC) and tire pressure
9	Expert	50 min	France	1	2008	ADAS for safety speed
10	-	1h00	France	2	2019	ACC for manual gearbox, breaking system assistance

Table 2 – Interview details

[9] In particular, two co-authors were involved in multiple previous longitudinal research partnerships on engineering capability since 2005, and one co-author is currently involved in another research-action project with Renault and is integrated in the incumbent team, which guaranteed a understanding of the context of this specific incumbent and field access.

[10] As Renault has an Alliance with Nissan, some AI-based patents were co-filed by both companies, with Renault affiliated inventors only based in Japan.

[11] As some inventors filed more than one patent families, we contacted in priority those with multiple patents to cover a maximum of the AI-based invention patent portfolios. E-mail answers have been also included in our analysis.

[12] See table 2 of interview details for application dates of patents

4. RESULTS FROM QUANTITATIVE ANALYSIS

4.1. Descriptive statistics regarding AI-based patents

As shown in **Figure 1**, there has been a significant increase of AI-patent families field by selected automotive incumbents during the 2005-2020 period, with a remarkable speed-up during the period 2013-2020. Nevertheless, those incumbents' share of AI-based patent remains limited: they filed 86.2 AI-based patent families per year between 2005 and 2020 on average, accounting only for 4% of all patent families filed each year[13].

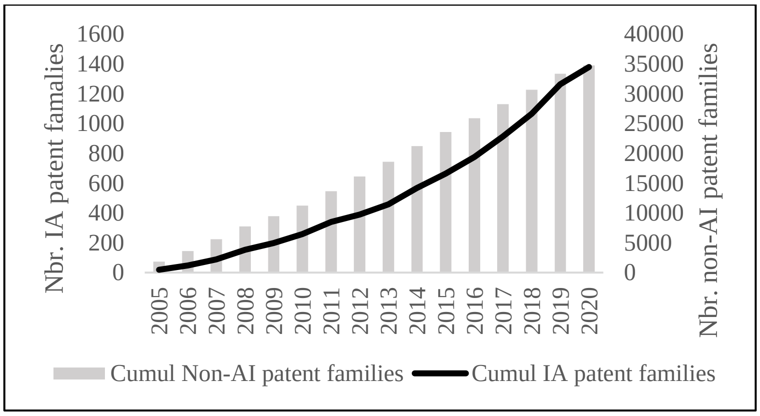


Figure 1 – Evolution of AI-based and non-AI-based patent families since 2005.

4.2. Knowledge search practices of automotive incumbents

By relying on the procedure developed in the methodology section, we are able to classify each invention between four knowledge search practices. In **Table 3** we present the number of patent families classified in each knowledge search mode.

Throughout our analysis, we showed no significant variations between the knowledge search modes used by major incumbents from the automotive industry for AI-based invention or for non-AI-based inventions, including inventions for EV propulsion. **Indeed, nine patent families out of ten are based on an exploitation strategy. In other word, no additional**

[13] The details per company is available on Appendix 1.

knowledge component appears in the knowledge base through those inventions and no new distant combinations of knowledge are created. Although, the phenomenon is not astonishing for non-AI-based data as we posit that incumbents are known to extensively rely on their pre-existing knowledge by adoption knowledge-depth strategies (e.g., Katila and Ahuja, 2002), it is surprising for AI technologies. Indeed, it means that AI technologies that support the exploitation of big data are mainly used to improve pre-existing features' performances instead of opening more radical paths. Those elements conduct to reject Hypothesis 1: AI-based inventions do not lead automotive incumbent to access extensively to new knowledge and create novel distant combinations of expertise.

As we observed similar innovation paths between the three patent categories, we can also posit that AI technologies are not integrated into the NPD process through an ad hoc procedure. We also highlight that there is still a difference in the exploitation mode of AI-based inventions. A more significant share of those patent families conducts to establishing AI-supported knowledge clusters through project KS mode (19.1%) compared to non-AI-based patents (9.6%) and electric battery patents (11.9%). Big data exploited through AI technologies favor the densification of local knowledge more extensively.

Knowledge search mode	Expl. degree	AI-based		Non-AI-based		Electric battery	
		Nbr. patents	Perc.	Nbr. patents	Perc	Nbr. patents	Perc.
Refinement	--	1,002	72.7%	28,782	82.9%	4,331	79.1%
Project	-	263	19.1%	3,342	9.6%	652	11.9%
Total exploitation		***1,265***	***91.7%***	***32,124***	***92.5%***	***4,983***	***91.0%***
Absorption	+	95	6.9%	2,136	6.1%	392	7.1%
Recomposition	++	19	1.4%	471	1.4%	102	1.9%
Total exploration		***114***	***8.3%***	***2,607***	***7.5%***	***494***	***9.0%***
TOTAL		1379	100%	34731	100%	5480	100%

Table 3 – Knowledge search used for AI-based, Non-AI-based and electric battery patents by automotive incumbents (2005-2020)

4.3. Technological originality

To test hypothesis 2, we measure incumbents' average technological originality level when they rely on different knowledge search modes. The mean ADOI score per knowledge search mode and category of the invention is presented through a graphical analysis in **Figure 2**. AI-based inventions conduct to a higher score of technological originality than EV propulsion or non-AI patents on average, confirming the highly innovative characters of AI-based patents.

We show that aligned with traditional assumptions, relying on more explorative strategies conducted to the highest level of technological originality for non-AI based inventions (0.58 vs. 0.41), including for electric batteries (0.57 vs 0.46). But the case of AI-based inventions appears unique as explorative strategies conduct to a similar technological originality level than more exploitative strategies (0.76). Hence, we do not validate Hypothesis 2: **incumbents from the automotive industry derive at least a similar innovative value from their invention when they implement AI-based technologies in pre-existing features through exploitative strategies than when using (rarely) more explorative ones**.

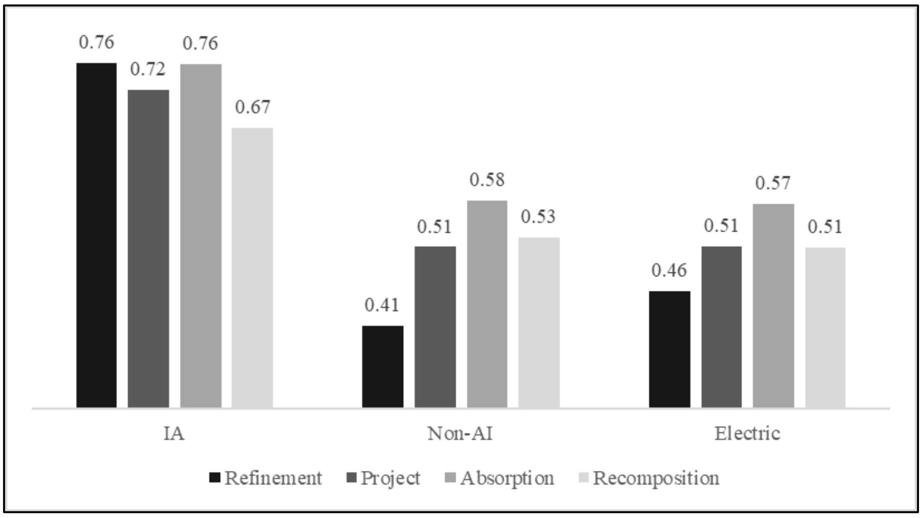


Figure 2 – Repartition of ADOI scores per KS modes and type of patent families (2005-2020 period, multi-IPC-classes patent families only)

Finally, the quantitative analysis conduct to invalidation of Hypotheses 1 and 2. This is in line with the challenges raised regarding incumbents' knowledge bases and imprinting issues,) specifics from big data innovation, and automotive industry NPD process issues. **Our quantitative analysis shows that AI-based inventions do not lead extensively to radical paths and instead is implemented through a traditional automotive NPD process**. But such exploitative path still leads to valuable and original inventions, while non-AI and EV propulsion patents mainly conduct to valuable and original inventions through more explorative paths.

5. QUALITATIVE ANALYSIS

To better understand the findings of the quantitative study, we report in this section the results of the interviews, with qualitative data collected from Renault's inventors of AI-based patents. Exemplary quotes illustrate our findings and are chosen based on their representativeness and clarity.

5.1. A "problem-solving approach" usage of AI technologies during the final phase of new product development cycles

5.1.1. Motivations for AI integration into inventions

Based on the qualitative evidence collected, we were able to distinguish between three motivations for AI technologies integration in inventions.

First, we found qualitative evidence that AI technologies were integrated into inventions to improve passenger's comfort after issues were raised following the testing phase. In those cases, the key objective was to solve the negative feedbacks reported from the testing phase of already industrialized vehicles as mentioned by one informant:

> *[We undertook] an entire study on driving discomforts, the situations in which people were in a condition of discomfort, to identify what we could do to limit or avoid those discomforts in terms of technical solutions. (Interview #4)*

Hence, this case of AI integration is mainly related to issues that arise following the development of new innovative features regarding ADAS or more autonomous vehicles, as the client asked to trust the system and live a comfortable driving experience. Here, inventors decided to capitalize on AI technologies to deal with negative feedback and offer clients a better driving experience.

Second, AI technologies have also been used to solve minor sensors or mechanical issues. For example, as many ADAS systems were developed based on integrating new sensors, issues regarding their quality can affect the integrity of the designed feature. One informant proposed an illustrative example:

> *In fact, those technologies are not super robust, and what we called a gosht could occur, which means that [the sensor] would tell you "I detected something [a barrier], behind or beyond the car during a very short time". It will tell you there is a barrier at 50 centimetres of your car. But some time later, this barrier disappeared. So it is what we call a ghost. […] Because for us, visually, we do not see anything but the sensor sees it. (Interview #1)*

In those cases, AI technologies have been creatively used to revise issues that engineering teams faced related to sensors or mechanical elements limitations or integration in a new use case.

Third, interestingly, for some AI-based inventions, the main motivation was to favor cost reductions strategies. For example, one objective can be to reduce (or even entirely delete) the number of sensors used for a given feature by relying on AI technologies, as described by one informant:

> *I delete my sensor because I do not need something very accurate, and a model can do that. […] The first idea, which was an estimator based on an algorithm, we developed it. […] The goal was to delete the sensor. (Interview #7)*

One interesting element is that such inventions for which the primary motivation is cost-saving are not ultimately integrated into the vehicle but can only be used for negotiations with the OEMs, as illustrated by the following quote:

> *Finally, we did not use [the patent] either. That is to say, it is not a patent that we exploit, because at the end, the strategic choice of the company, was to buy that [the sensor] in a tiers-one or tiers-two. But, anyway, it was useful to negotiate the price [of the sensor], of course. (Interview #8)*

Finally, we found qualitative evidence that Renault used AI technologies to solve quality issues identified following a testing phase as passenger comfort issues, minor mechanical or sensors failures, or even to pursue cost-saving strategies.

5.1.2. AI integration for problem-solving in industrialisation phase of NPD projects

One common point between the different motivations for AI integration in inventions at Renault is that it systematically occurs at the end of the NPD process: AI is integrated in industrialization phase of the project instead of being a prerequisite or a specification made during the upstream design phase of research and advanced engineering. Then, as the project for a new vehicle is on the pipe for a long, inventors are committed to fix local technical problems raised during the last development phase. Many inventors explained that when they designed their inventions, it was related to vehicle projects for which the technical definition phase had already been completed:

> *You should know that we were already industrializing the car, we do not have time to review the sensors for redesign purposes. We were with the sensors bound hand and foot. (Interview #1).*

Interestingly, those inventors have used radically new technology to solve the issues they were facing, but as the reported problems were locals, it led to design fixations limiting the possibilities for pursuing more radical paths (Agogué et al., 2014; Le Masson et al., 2010). This problem-solving logic of IA integration was reported by many inventors, corroborating the exploitative logic of working on fixing "*well-known issues*" (Interview #7). The following quote illustrates adequately this perspective:

> *It is not necessarily a lack of honour for AI, but… AI tends to solve already existing problems, not problems that do not exist. […] The perfect autonomous vehicle is just a driver. So forcibly, it does not do more than a driver […]. AI only solved existing problems. (Interview #7)*

Thus, inventions integrating AI technologies are not based on the demand or proposal of Research and Advanced Engineering teams responsible for designing new features (Maniak et al., 2014), which would have corroborated an ambidextrous approach.

Finally, AI-based technologies are mainly used during the industrialization phase, as a patch to solve local problems. But it still conducts to valuable creative paths as inventors explore locally by using AI technologies to address the raised issues. However, to go a step forward, we need to understand better the factors that limit the development of more radical explorative paths when automotive incumbents rely on AI-based technologies, and the next challenges to benefit of AI integration.

5.2. Next challenges to benefit of AI integration

We found qualitative evidence that a more intensive usage of AI technologies for big data could be desirable to develop new innovations. But some technical and organization challenges need to be tackled, that we identified in our interviews.

5.2.1. Technical factors: from raw to valuable data

Informants largely agreed that due to the high number of sensors, automotive companies collect data more extensively, leading to big data sets. But interestingly, they also reported that more valuable datasets need to be gathered to favor more innovative approaches. The main issue raised concerned either (1) the lack of labelled data to perform AI-based analyses, and (2) the capacity to bundle different sources of data.

Firstly, while Renault is involved in the process of gathering large amount of information through sensors and cameras during the testing process or in operation, it mainly constitutes raw data that are not appropriate for further AI-based analyses. As indicated by one autonomous vehicle expert:

> *Because for example, [my teams] always say that they have significant difficulties labeling the rolling testing. It means that they have hours and hours of rolling testing. And for example, here, if we create an algorithm for multi-turns, you need a person that watches the camera when the multi-turns occur, to note that in the database, and that is apparently something very time-consuming. (Interview #8)*

Secondly, another issue raised to provide more valuable datasets concerns the capacity to bundle different data sources. The main mechanisms for ADAS functions were based on a "one sensor for one action" logic (including possible safety loops). But the multiplication of sensors implies an increase of the data sources available for one decision to be taken by the algorithm. It constitutes an ad hoc technical challenge as reported by one informant:

> *It means that you need to add sensors, radars, ultrasounds, etc., and we start to have many sensors. And it is there where for example, AI algorithms could already provide much help for the fusion of data part. [It could help to attempt] being capable of treating things that today, we are incapable of doing… Because fusionning data, already, is a big big challenge (Interview #8).*

These databases fusion issues appear critical and require both technical advances and the constitution of ad hoc expertise. For example, it requires higher calculation speed and companies need to constitute a team of data-fusion specialists, notably by hiring experts, an action recently started as reported by one informant:

> *And then, me, when I hired… the last wave of hiring I participated in, it was people with competencies to develop algorithms to fusion data from the sensors (Interview #9)*

But despite those technical challenges to go from raw data to more valuable data that would empower AI-experts to better benefit from AI, organizational factors were also identified.

5.2.2. Organizational factors: a lack of automotive company support for AI-based approached

First, informants question the responsibility for data-driven innovation in the automotive industry value chain. While most of the data are collected through vehicles sensors, some inventors claim that OEMs are those who need to foster AI-based innovation, or that car manufacturers should team up with OEMs. One reason claimed for such labor division is that usually when they partner, car manufacturers are not incentivized regarding patents or potential licensing fees as the OEMs mainly remain the final assignee. As raised by one informant:

> *It is more the suppliers who are responsible for the development of the intelligent part of the sensor. They will be consumers of AI methods. We, only the data-fusion part. (Interview #9)*

But our quantitative findings show that it is not the case as OEMs filed only 14% of AI-based patent families, and co-patenting are limited.

Second, it is worth noticing that while informants have been retrieved through a careful identification of AI-patents based on a query developed by an international organization, the WIPO, a large part of them do not feel that they contribute to AI. The point was first raised in the e-mail exchanges with the informants prior to the interviews, but also during the interviews. As mentioned by one informant:

> *I do not consider myself as someone active in the AI community […] We did not develop this patent with Gerard*[14] *by telling each other "we do an AI patent". (Interview #2)*

Two phenomena can explain this feeling of not contributing to AI-based inventions. On the one hand, AI technologies are mainly used by inventors active in the ADAS landscape, and they mainly consider AI as an incremental innovation or a sort of "buzz word" in their field. The breakthrough technology of AI does not conduct to radical innovation as there is no major change of the object identity (Le Masson et al., 2016), i.e. the vehicle itself. As mentioned by one ADAS specialist:

> *To tell you, I have some troubles telling the difference between AI and lots of other things […]. Today, we speak of AI to put some words on things that we also did before […], which we named differently […] but already existed. So honestly, from what I know, […] there is no major breakthrough, we can say it like that, which justify calling that AI. (Interview #4)*

[14] Name has been changed for confidentiality

Hence, AI is not considered a new technology per se as it has been included as part of the ADAS expertise, and it can limit the commitment to rely on AI technologies to follow more disruptive paths. On the other hand, while the WIPO definition of AI includes all sorts of AI-based technologies (fuzzy logic, search methods, logic programming, etc.), most informants consider that AI is only related to neural networks and therefore consider that they do not contribute to this field, as illustrated by the following quote:

> *There is no neural network beyond the solution that has been proposed. And know that you say [that the patent related to AI], I am telling me that yes, in fact, we could… but no, we used old traditional methods for that patent. So it is quite surprising that it has been categorized as an AI-based patent, but I am telling myself that it is not that impossible in the end. (Interview #1)*

This feeling can conduct to a detrimental lack of expertise recognition and limit their capacity and legitimacy to propose more disruptive innovation that gather a diversity of such breakthrough technologies for car development

Finally, while automotive incumbents face both technical and organizational factors to explore more radical paths with AI technologies, as retrieved in our qualitative investigations, AI and big data still appear in their infancy. As raised by one informant:

> *There are around 3-4 years, we thought that in the coming years, we would have autonomous vehicles… today, it still is not the case, so we are still focusing on improving what is existing, taking into account new use cases, etc. So the real disruption from AI, I think […] it will come up soon, […] but here, we are more on new functions, for which we can say, that there is no much disruption (Interview #10)*

6. DISCUSSION

6.1. Theoretical and empirical contributions

First, we contribute to the knowledge search literature by showing that big data and the AI technologies that support the digital transformation of automotive incumbents change the way knowledge search practices are evaluated for innovation performances. In our case, incumbents intensively exploit their knowledge through AI and big data in creative and valuable way, while minimizing their exploration effort. These findings echo Katila and Ahuja (2002), who showed that while "old" knowledge can hurt innovation through obsolete activities, it can also help as it appears highly reliable.

Second, we contribute to the digital innovation literature by demonstrating that the NPD process that supports big data and AI-technologies implementation is divergent from the traditional approach with radical and generative technology implementation. As in many other industries, the automotive sector created successful innovation by relying on an ambidextrous system (Lo and Theodoraki, 2021; Maniak et al., 2014). Bun the case of big data and AI technologies, the approach appears different: big data or AI technologies integration into vehicles is not a prerequisite asked during the upstream phase by the Advanced Engineering Team. Instead, it is implemented at the end of the process to solve local and minor issues related to sensor accuracy or passenger comfort after testing phases. To our knowledge, this bottom-up approach of integrating emergent technologies in the NPD process appears relatively new in the literature.

Third, our study demonstrates that we are in the presence of an elusive AI and big data fad in the case of incumbents from the automotive industry. Indeed, data-driven innovation is presented as the only path to tackle the creative industry challenges of the connected car, autonomous driving, and shared mobility. But, today, big data and AI technologies are still in their infancy. While they favor the local creative approach, their utilization is almost restricted to strengthen the pre-existing ADAS during the industrialization phases of the NPD process.

6.2. Limits and rooms for further research

Despite the richness of the mixed-method approach, our investigations present some limitations and open room for further research in this area.

First, while our quantitative analysis is based on the top-19 innovative incumbents in the automotive industry and their usage of big data and AI technologies, we restrict our analysis to patent data only. Other data sources could be used to complement our research (incumbents' internal data such as financial amount or team structures and profiles dedicated to data-driven innovation, roadmaps, and investment plans). Relying on other data sources could help to better understand data-based innovation for incumbents less involved in such activities or 2nd or 3rd order OEMs. Second, our qualitative analysis was based only on one case study while carefully selecting the incumbent. We then call for further qualitative studies on automotive incumbents' data-driven innovation and NPD processes. Third, Additional studies could also integrate the newcomers, notably originated from internet companies (Google, Uber).

Finally, this global investigation sheds light on new valuable knowledge search practices used by automotive incumbents to integrate big data and AI technologies in vehicles by relying on new NPD bottom-up approaches. The authors believed that future research should complement our effort by analyzing if this blurred frontier between exploration and exploitation that arise from the digital transformation can be identified in other historical industries (e.g., plane) and with other emergent technologies (e.g., hydrogen related technologies).

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8. APPENDIX

Company	Type of company	AI patent families	Non-IA patent families	EV propulsion patent families	Share of IA patents families	Share of IPC covered by AI patent families
Porsche	Manufacturer	407	5113	542	7.96%	26.67%
Nissan	Manufacturer	189	2003	673	9.44%	23.87%
Toyota	Manufacturer	150	5588	2146	2.68%	20.28%
Valeo	OEM	111	2857	117	3.89%	16.30%
BMW	Manufacturer	99	1727	270	5.73%	18.13%
PSA	Manufacturer	65	2055	101	3.16%	13.73%
Renault	Manufacturer	64	1781	275	3.59%	13.29%
Honda	Manufacturer	54	2443	431	2.21%	21.69%
Daimler	Manufacturer	47	1259	137	3.73%	13.85%
Aisin Seiki	OEM	43	2027	387	2.12%	19.69%
Stellantis	Manufacturer	42	1608	84	2.61%	8.81%
BorgWarner	OEM	38	656	57	5.79%	13.85%
Mazda	Manufacturer	30	557	42	5.39%	13.00%
Ford	Manufacturer	18	535	36	3.36%	10.53%
Hyundai	Manufacturer	8	203	60	3.94%	9.89%
Brigestone	OEM	6	2746	12	0.22%	6.58%
General Motors	Manufacturer	4	541	7	0.74%	8.41%
Yazaki	OEM	3	716	93	0.42%	7.53%
Safran	OEM	1	311	10	0.32%	4.39%

Appendix 1 – AI, Non-AI and electric battery patent families filed per company (2005 – 2020)