Cross-boundary AI Innovation as Recombinant Search in Heterogeneous Landscapes: A Network Analysis of Computer Science and Autonomous Vehicle Fields (2009-2020)

Kaige Gao*
Weatherhead School of Management, Case Western Reserve University
kxg297@case.edu

Dongyeob Kim*
Weatherhead School of Management, Case Western Reserve University
ddk52@case.edu

Zhewei Zhang
Warwick Business School, University of Warwick
Zhewei.Zhang@wbs.ac.uk

Youngjin Yoo
Weatherhead School of Management, Case Western Reserve University
yxy23@case.edu

ABSTRACT

AI has rapidly penetrated various industries, hailed as a universal problem-solving tool. Scholars have studied AI innovation across the contexts of their development and implementation. As general-purpose technology, however, AI innovations need to first jump across its disciplinary boundaries before they can subsequently become useful as applications. To unpack how such jumps are made, we conceptualize cross-boundary AI innovation as an outcome of recombinant search in heterogeneous innovation landscapes that are, in turn, comprised of a set of interconnected epistemic objects. We take a dynamic network view as an analytical perspective

* These authors contributed equally to this work.

and identify two structural attributes: structural embeddedness and junctional embeddedness, which represent its popularity and role as a bridge, respectively. To assess their impact on the likelihood of a jump by an epistemic object, we test our theory using a data set of AI-related journal and conference articles from both Computer Science and Autonomous Vehicle fields in the period from 2009 to 2020. Our results show that junctional embeddedness has a positive impact on an epistemic object's jump particularly in the early periods of time, while the effect of structural embeddedness varies over the periods.

Keywords:

AI/ML, Diffusion of Innovation, Network Analysis, Recombinant Search

INTRODUCTION

Heralded as a "general-purpose technology with espoused vast application" (Anthony, Bechky, & Fayard, 2023: 3), AI is seen as a panacea for all problems facing humanity. In a recent blog, Marc Andreessen, a celebrated venture capitalist, states: "We believe Artificial Intelligence is best thought of as a universal problem solver. And we have a lot of problems to solve…There are scores of common causes of death that can be fixed with AI, from car crashes to pandemics to wartime friendly fire" (Andreessen, 2023). However, to realize its potential as a solution, AI must meet with a real problem that often resides outside the AI field.

Scholars have studied various challenges of managing AI innovations. On the one hand, studies that focus on the *development* of AI have alluded to emergent issues in relation to its goal definitions (Verganti, Vendraminelli, & Iansiti, 2020; Zhang, Hummel, Nandhakumar, & Waardenburg, 2020), the bias inherent to the training of models (Faraj, Pachidi, & Sayegh, 2018), and the contested nature of its performance evaluation (Lebovitz, Levina, & Lifshitz-Assaf, 2021). On the other hand, others have provided insights into the *implementation* challenges of AI innovation, such as the influence of algorithmic opacity on user adoption (Jussupow, Spohrer, Heinzl, & Gawlitza, 2021), as well as unintended consequences of changed work arrangements (Pachidi, Berends, Faraj, & Huysman, 2021). We argue, however, that before AI innovations can be configured via subsequent development and implementation in specific organizational contexts (Glaser, Pollock, & D'Adderio, 2021), advanced AI *innovations* from the computer science field must first cross its disciplinary boundaries and jump to other domains to become useful as applications (Boland Jr & Tenkasi, 1995; Garud, Tuertscher, & Van de Ven, 2013). Yet, we know little about *under which conditions cross-boundary AI innovations occur*.

To address this question, we view cross-boundary AI innovation as an outcome of a recombinant search between multiple innovation landscapes (Fleming, 2001; Levinthal, 1997). Each innovation landscape is constituted by a set of interconnected *epistemic objects*. An epistemic object refers to open-ended concepts or components that embody an element of scientific knowledge (Knorr-Cetina, 2016). As the relationships between epistemic objects are changing over time, we take a dynamic network view on landscapes as an analytical tool to conceptualize jumps of epistemic objects between networks as indicative of cross-boundary innovations (Wang, Rodan, Fruin, & Xu, 2014). We theoretically develop and identify two structural attributes of an epistemic object within a network, i.e., its popularity and role as a bridge, that enhance its likelihood of making a jump across networks by signaling usefulness to cross-boundary innovators conducting the search.

To test our theory, we select the Computer Science (CS) and the Autonomous Vehicle (AV) fields to represent two distinct innovation landscapes where cross-boundary innovations take place.

We use a unique dataset of articles published in top AI-related journals and conferences in each field, covering the period between 2009 to 2020. Using the dataset, we construct two networks to capture both fields, where a node represents an epistemic object and a tie between two nodes results from their combinations within a network in previous years (Wang et al., 2014). Finally, we identify that a jump of an epistemic object across boundaries has been made when the node appears in the other network, thereby indicating the occurrence of a cross-boundary innovation.

After a brief review of recent research on AI and cross-boundary innovation, we conceptualize cross-boundary innovation as a recombinant search in heterogeneous landscapes. We then develop our hypotheses using a network approach to innovation landscapes. After presenting the results of our empirical study and robustness checks, we conclude the paper by discussing the implications of our findings.

RELEVANT LITERATURE

Challenges of Artificial Intelligence Innovation

AI refers to "highly capable and complex technology that aims to simulate human intelligence" (Glikson & Woolley, 2020: 627). Scholars in the management and information systems (IS) fields have studied the challenges associated with the management of AI technologies across different processes of innovation (Berente, Gu, Recker, & Santhanam, 2021; Garud et al., 2013).

On the one hand, prior research has highlighted the challenges associated with AI development that mainly emanate from leveraging and assessing unique types of learning by human workers and machines. Zhang et al. (2020) suggest that three key challenges of developing a machine learning (ML) system are: 1) defining the ML problem, 2) managing the training of the machine learning model, and 3) evaluating the performance of an ML system. First, with the advancements in generative AI that are capable of performing tasks that were traditionally considered as involving 'creativity' without extensive reliance on human designers (Baird & Maruping, 2021; Seidel, Berente, Lindberg, Lyytinen, Martinez, & Nickerson, 2020), the role of humans in goal definitions and creating the right 'problem-solving loops' for machines are argued to be particularly important (Brynjolfsson & Mitchell, 2017; Verganti et al., 2020). For example, rather than being involved in every step of the chip design process, a designer's role has changed to focus more on specifying and tweaking design parameters for self-learning algorithms (Zhang, Yoo, Lyytinen, & Lindberg, 2021). At an organizational level, Li, Li, Wang, and Thatcher (2021) similarly highlight the importance of chief information officers (CIOs) for developing a firm's AI orientation, i.e., the overall strategic direction and goals around the application of AI technologies for solving business problems. Second, the difficulties associated with the training of AI models owe largely to the input data. The notion of raw data is argued to be an 'oxymoron', given that data and the algorithms that use it are never pure from value choices that reflect personal beliefs and political qualities, whether intendedly or unintendedly (Faraj et al., 2018; Martin, 2019). In particular, Kellogg, Valentine, and Christin (2020) caution that inequalities in work settings may be reinforced beneath the façade of 'rationality' of managerial decisions imbued in algorithms. Third, evaluation routines in AI development are ambiguous and contested by different stakeholders (Garud & Rappa, 1994). Lebovitz et al. (2021) show that the accuracy of 'know-what' embedded in ML-based tools was evaluated by the 'Area Under the receiver operating Curve (AUC)' measure, which was not necessarily connected with the tacit 'know-how' of human experts in practice. Similarly, Van den Broek, Sergeeva, and Huysman (2021) illustrate the challenges ML developers face in managing the tension of producing knowledge independent of and in relevance with domain experts.

On the other hand, studies that examine the implementation of AI have shed light on the challenges that arise with respect to 1) user adoption and 2) organizational changes. The delivery of accurate algorithmic predictions *per se* is rarely sufficient in fostering effective human-AI collaboration, and users may resist AI adoption if they do not understand its capabilities nor see its utility over existing practices (Cai, Winter, Steiner, Wilcox, & Terry, 2019). Given the opacity of algorithmic processing and output, human users use second-order cognitive processes to decide whether the AI advice will be accepted or rejected (Jussupow et al., 2021). Likewise, even among occupational groups of similar backgrounds and needs, Lebovitz, Lifshitz-Assaf, and Levina (2022) found that only one group saw the benefits of engaging in 'AI interrogation practices' to reconcile their knowledge claims with those of AI. It could also lead to potentially problematic circumstances as users blindly accept AI output, as they start behaving like 'borgs' and lose the strengths of unique human knowledge at the gain of stronger individual performance (Fügener, Grahl, Gupta, & Ketter, 2021); even knowledge workers, who are assumed to actively avoid the such, are not exempt from this shortcoming (Anthony, 2018). Moreover, the implementation of AI technologies may raise further potential issues for the organization. Where the workers only pretend to accept and use undesirable algorithms in conforming with managerial suggestions, it could inadvertently lead to full implementation of the system as it appears ostensibly effective (Pachidi et al., 2021). This could result in a new power imbalance where one occupational group becomes privileged over others in the changing work arrangements (Orlikowski & Scott, 2015; Waardenburg, Huysman, & Sergeeva, 2022). To reap the full benefits of AI implementation, the organization additionally must devise a 'hybrid practice' that paves new interaction paths between the system and the human workers (Raisch & Krakowski, 2021; Van den Broek et al., 2021; Willems & Hafermalz, 2021).

Notwithstanding the contributions of prior works, less has been studied on managing AI technologies in their capacity as *inventions* (Garud et al., 2013). AI is conceptualized as a general-purpose technology that can be applied in a broad range of applications (Anthony et al., 2023; Bresnahan & Trajtenberg, 1995). While new promising AI technologies are invented by actors in the computer science field, they must first undergo the process of crossing disciplinary boundaries from computer science to other application domains before further developments and implementations can be made within organizations. In this study, we therefore seek to address how AI inventions may successfully cross borders and be repurposed for potential applications.

Cross-boundary Innovations

Earlier innovation studies literature has shown that the progress of technological innovation is defined by its trajectory (Dosi, 1982). The process can be viewed as linear, in which relevant problems to be addressed, material artifacts themselves, and the procedural knowledge in evaluating them become gradually negotiated and refined among diverse stakeholders (Bijker, 1997; Garud & Rappa, 1994). With ongoing R&D investments, the new technology reaches maturity when all feasible improvements in its performance dimensions have been realized. The deepening understanding and beliefs by the industry actors about the technology can preempt the recognition of alternate possibilities that are perceived as not aligning with the existing dominant design (Garud & Rappa, 1994; Tripsas, 2009).

A shift in an innovation trajectory is needed to trigger a discontinuity and break away from the established institutions (Anderson & Tushman, 1990). Trajectory shifts occur as innovators recognize the limitations of the present and envision a possible future that involves learning about and the adaptation of new technologies (Henfridsson & Yoo, 2014). These periods are marked by the innovators' struggles in aligning an alternate technology to gain acceptance by the very industry and institutions they are attempting to disrupt (Hargadon & Douglas, 2001). Such innovators are usually industry outsiders possessing different capabilities and experiences and can offer unique knowledge of different existing technologies for those that reside within an industry (Hargadon & Sutton, 1997; Kaplan & Tripsas, 2008). For example, the emergent features of digital cameras were influenced by the prior affiliations of different firms from the photography, consumer electronics, and computing industries (Benner & Tripsas, 2012).

As such, the source of breakthroughs mostly comes from innovations that occur across the boundaries of disciplines and specializations (Carlile, 2004). Contrary to the myth of an isolated genius inventor, Fleming and Singh (2010) argue that the likelihood of novel creation is enhanced when innovations are produced by collaborators from diverse disciplinary backgrounds. This is especially important as the complexity of contemporary innovations requires the involvement of heterogeneous actors that transcend the boundaries of a single 'community of knowing' (Boland Jr & Tenkasi, 1995). The development of a 'smart city' for instance, requires various experts from the technology, sustainable development, and real-estate domains to be brought together (Zuzul, 2018). The trajectories of different innovations stemming from such multiple boundaries can thus be suggested to intermingle with one another and lead to wakes of trajectory shifts (Boland Jr, Lyytinen, & Yoo, 2007; Oborn, Barrett, Orlikowski, & Kim, 2019).

Cross-boundary innovations have become particularly salient with the pervasiveness of digitalization. While the architectures of industrial innovations are frozen for a suitable period of time before they can be redesigned, the non-material qualities of digital technologies allow for a seamless convergence of components from previously separate industries in creating innovations

(Henfridsson, Mathiassen, & Svahn, 2014; Yoo, Boland Jr, Lyytinen, & Majchrzak, 2012). Digital innovations involve many interdependent actors applying their solutions to problems found across a loosely coupled ecosystem (Wang, 2021). Scholars have thus even suggested that digital technologies blur and dissolve the conventional notion of industrial boundaries (Drechsler, Gregory, Wagner, & Tumbas, 2020), facilitating the process whereby innovators search for and explore a more eclectic range of components beyond their traditional domain.

THEORY DEVELOPMENT

Innovation as a Recombinant Search

We conceptualize an innovation as a recombinant search process (Fleming, 2001). Actors begin searching for new solutions in another domain when the old technology is perceived as having reached its limits or due to shifts in user preferences (Kaplan & Tripsas, 2008). This can involve searching for a new combination of components or a new relationship among previously combined components (Henderson & Clark, 1990). A component innovation occurs as innovators search for an individual component to replace an existing one in a product, such as a new engine in an automobile. The latter, on the other hand, involves the changes in the linkages among components, which could also involve incremental modifications or redesign in the components to fit the new architecture; the goal of this search may be to improve the performance of a product or to ease the coordination efforts for problem-solving (Albert & Siggelkow, 2022).

Actors may choose to pursue a local or distant search for new combinations (Fleming, 2001; March, 1991). In the case of the former, innovators select and recombine more familiar components, which is likely to lead to more incremental innovations. While a local jump is suggested as the predominant method in innovation given the less uncertainty involved, continually working with a set of familiar components may lock innovators into a single way of thinking and preempt them from potentially more useful opportunities for a breakthrough (Fleming & Sorenson, 2004). On the other hand, combining knowledge from technologically diverse and distant spaces is argued as more likely to produce innovations that break away from an intellectual lock and lead to novelty, consistent with the arguments of cross-boundary innovations (Hargadon & Sutton, 1997; Kaplan & Vakili, 2015).

The concept of innovation landscape is used to conceptualize the space in which recombinant search processes take place and better inform innovators' decisions on undertaking local or long-jump searches. Following the work of Kauffman (1993), scholars have used NK models to simulate landscapes (Fleming & Sorenson, 2001; Levinthal, 1997). The outcome of the search process is influenced by the topography of the landscape, where smoother, non-rugged landscapes pose less risk for innovators pursuing incremental innovations via local search (Fleming & Sorenson, 2001, 2003). Despite its higher risk, however, successful distant search in rugged landscapes also offers the innovator with higher potential for a breakthrough. To minimize the unpredictability of navigating through rugged landscapes, Fleming and Sorenson (2004) illustrate that scientific research can play the role of a 'map' for innovators. Rather than blindly searching for new technologies, science can offer them some visibility of the landscape and prevent them from searching in inefficient directions or being trapped in local optima.

The scope of existing studies that draw on the recombinant search notion is largely limited to innovations within a single domain. However, cross-boundary innovations differ in that they entail interactions between multiple heterogeneous landscapes, instead of a single landscape of within-domain innovations. Where innovators in the latter conduct their search within the boundaries of their landscape (Fleming, 2001), cross-boundary innovators can be viewed as conducting their search for both new solutions or problems in a foreign landscape, in addition to their landscape (Benford & Snow, 2000; Kaplan & Vakili, 2015). This resonates with the argument of Von Hippel and Von Krogh (2016) that the landscape metaphor should be expanded to encompass two separate landscapes that each represent the need and solution space. As such, the strategic recommendations by Fleming and Sorenson (2003) on pursuing local or distant search according to the landscape topography, may not necessarily hold when heterogeneous landscapes and their changing topographies are under consideration.

The presence of heterogeneous landscapes suggests that innovators are required to tap into a wealth of scientific knowledge in an external domain. For the boundary insiders who are progressively developing a finer language of their specialized domain (Boland Jr & Tenkasi, 1995), new advancements in scientific methods and knowledge can thus be fruitfully used as a map to find optimal combinations (Fleming & Sorenson, 2004). Such maps, however, can be less accessible to outsiders, as they bear the complex task of taking into account and translating the same knowledge into their boundaries (Boland Jr & Tenkasi, 1995; Carlile, 2004). For example, although the field of 'systems biology' emerged as an interdisciplinary study of biological systems from computational and mathematical approaches, Zou and Laubichler (2018) found that the field was initially dominated by systems-oriented components until the mid-1990s and has only seen a surge of biology-oriented components in recent years.

A Network Perspective on Innovation Landscapes

As innovation landscapes represent the space where innovators search for knowledge on new sources of recombination (Fleming & Sorenson, 2004), they can be described as being constituted by *epistemic objects*. Epistemic objects are elements of knowledge that embody what we do not yet know for sure, such as a social problem or a disease (Miettinen & Virkkunen, 2005).

As opposed to the fixed qualities of technical objects, epistemic objects are characterized as open-ended projections (Knorr-Cetina, 2016; Rheinberger, 1997). Epistemic objects may have multiple material instantiations across different fields, but their simultaneous lack of completeness of being makes them a central source of scientific advancements as they generate further concepts and solutions. Due to their "nonidentity with themselves" (Knorr-Cetina, 2016: 176), they can only be defined by their interconnected relationships with other epistemic objects in the landscape to produce contextual understanding and meaning. Furthermore, these relationships are dynamically changing with the emergence, mutation, and disappearance of new and old objects, thereby constantly altering the topography of the landscape (McCarthy, 2003; Um, Zhang, Wattal, & Yoo, 2022).

Innovation landscapes can, therefore, be expressed as a network of epistemic objects and their changing relationship. Epistemic networks differ from social networks in that they are "linkages between kernels of scientific and technological knowledge" (Wang et al., 2014: 484). In an epistemic network, a 'node' indicates an epistemic object embodying a concept or an element of scientific knowledge (Carnabuci & Bruggeman, 2009). A 'tie' that connects the different epistemic objects represents their previous combination within their landscape (Fleming, 2001). Ties thus represent the innovators' previous search efforts and beliefs in the fruitfulness of combining the two objects (Fleming & Sorenson, 2004). The epistemic network approach to innovation has been adopted by scholars across different contexts, including knowledge stock at a firm level (Schillebeeckx, Lin, George, & Alnuaimi, 2021; Wang et al., 2014), growth of technology domains (Carnabuci & Bruggeman, 2009), and product variety at an ecosystem level (Um et al., 2022).

While prior studies have mostly considered the presence of a single epistemic network, a cross-boundary innovation implies that the interaction between heterogeneous networks must be examined. Each network reflects a separate innovation landscape comprising distinct sets of epistemic objects that have not been recombined with the objects from the other. In the context of AI innovation, the network from the computer science field will be populated by concepts related to various techniques and algorithms. In contrast, the concepts in other application fields will pertain more to the problems they are trying to solve. Cross-boundary innovation can, therefore, occur when the two disparate networks become connected as an epistemic object makes a jump to another network (Von Hippel & Von Krogh, 2016). We identify a node that appears in another epistemic network as indicating that a jump has successfully been made and recombined with the epistemic objects in a new network. Jumps between networks can further be bidirectional, as innovators may have problems searching for a new solution or, conversely, those needing a problem to address with their solution (Benford & Snow, 2000).

How do epistemic objects jump from one epistemic network to another? Rheinberger (1997: 30) suggests that the status of an object is dependent on the place or "node" it occupies in a system. Consistent with this idea, we expect the structural attributes of the epistemic objects in their original innovation network to be an important predictor of a cross-boundary jump, as they cannot be considered in isolation (Knorr-Cetina, 2016). This requires a network embeddedness approach: identifying the attributes of an epistemic object in relation to the wider context of its network and examining the effects of such features on the likelihood of its jump to another network (Wang et al., 2014). In this study, we consider two salient types of network embeddedness that are likely to cue an object's usefulness to innovators searching across boundaries, i.e., structural and junctional embeddedness (Grewal, Lilien, & Mallapragada, 2006).

Among closely related epistemic objects that are purported to address a similar set of problems, their popularity within the network may influence their likelihood of jumping to another network (Wang, 2009). As cross-boundary innovators comparatively lack the specialized knowledge of a foreign domain and their native vocabulary (Boland Jr & Tenkasi, 1995), the higher visibility of 'shiny objects' may signal their perceived importance during the search process (Abrahamson, 1991; Piazza, Reese, & Chung, 2023). The popularity of an object in an epistemic network can be measured by its structural embeddedness, i.e., the "extent to which an entity is entrenched in a network of relationships" (Grewal et al., 2006: 1045). Nodes with higher structural embeddedness have a greater number of connections with other nodes in the network. Since the ties between nodes at a given point in time are an outcome of prior combinations (Wang et al., 2014), this implies that epistemic objects that score high on this structural attribute have been used more frequently by the within-domain innovators in their local search for familiar components. Scholars have suggested that cumulative repeated local search of the same components may lead to only a marginal value as possibilities of useful combinations become exhausted (Fleming, 2001; Rivkin, 2000), Nevertheless, even where certain elements of knowledge have already taken up 'black-boxed' qualities within a landscape (Latour, 1987; Rheinberger, 1997), their unfamiliarity in another landscape may make them again open-ended and indicate a potential for breakthroughs when combined with the innovators' domestic epistemic objects (Hargadon & Sutton, 1997). Thus, we hypothesize:

Hypothesis 1 (H1): *The structural embeddedness of an epistemic object will positively influence its cross-boundary jump.*

In addition, certain epistemic objects can function as a bridge through which other objects become connected, allowing a long jump. These epistemic objects occupy a central position in an epistemic network to generate more new combinations (Fleming, Mingo, & Chen, 2007). Such objects are particularly necessary for innovators that are pursuing a distant search combination given they are used to fill structural holes, i.e., disconnections between nodes that represent a recombinant opportunity that has yet to be exploited (Wang et al., 2014). The bridge attribute can be captured by higher junctional embeddedness within a network, i.e., the "extent to which an entity connects other entities" (Grewal et al., 2006: 1045). While the exploration of popular epistemic objects may offer a viable initial entry point into another landscape, cross-boundary innovators are similarly likely further to require the use of objects with higher junctional embeddedness. This grants them access to other distant nodes for potential combination with nodes within their network. In the context of AI, while algorithms such as 'generative adversarial networks' may be highly popular at a given period, importing and repurposing them into a new landscape necessitates cross-boundary innovators to explore those that serve more as fundamental building blocks. Thus, we hypothesize:

Hypothesis 2 (H2): *The junctional embeddedness of an epistemic object will positively influence its cross-boundary jump.*

RESEARCH DESIGN

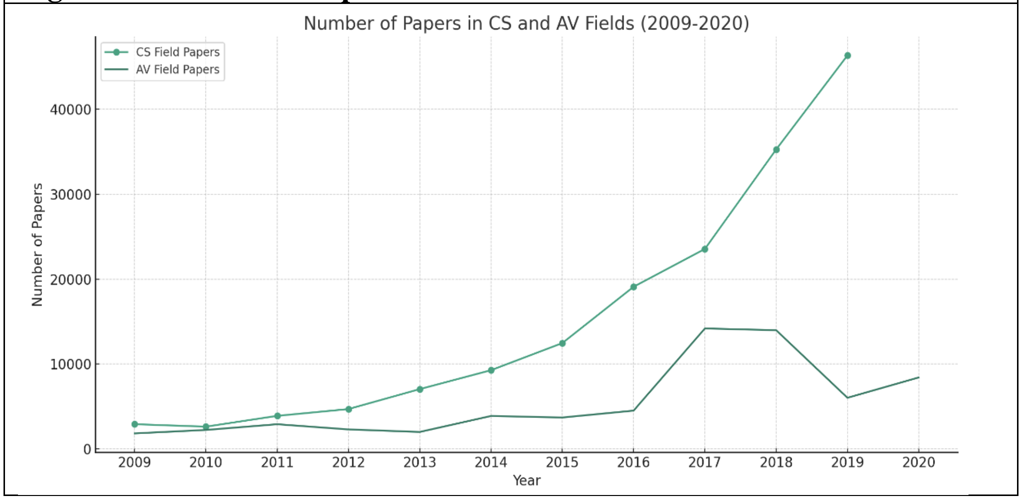
Data

In this research, we take a network perspective to understand the cross-boundary jumps of epistemic objects across two distinct fields: Computer Science (CS) and Autonomous Vehicles (AV). Consistent with their definition as elements of knowledge (Miettinen & Virkkunen, 2005), we used academic paper keywords to operationalize epistemic objects. To construct the dynamic epistemic network of these two fields, we first selected top-tier journals and conferences in AI-related areas of CS and AV, based on their ranking scores in Google Scholar's top publications. This selection criteria ensures a comprehensive and representative dataset of objects within these domains. The specific journals and conferences chosen are detailed in the appendix.

Our data collection involved gathering paper information from the OpenAlex database (https://openalex.org), which included paper titles, authors, publishers, and abstracts. To enhance the accuracy and breadth of our dataset, we supplemented this data with additional information sourced from the PapersWithCode website (https://paperswithcode.com). This dual-source methodology enabled us to gather a wide spectrum of academic papers and enrich the diversity and comprehensiveness of our research material. We paid special attention to the time frames for data collection in each field. For CS, our dataset spans from 2009 to 2019, while for AV, it extends from 2009 to 2020. The rationale behind this staggered timeframe is to capture the potential lag in concept jumps from CS to AV, allowing us to trace the trajectory and impact of these cross-boundary conceptual shifts more accurately.

Our final dataset comprises 167,164 papers from the CS field and 65,967 papers from the AV field. Figure 1 illustrates the annual distribution of these papers. Many journals offer a predefined list of keywords, and these controlled vocabularies are designed to standardize keywords across publications. However, such broad keywords may not fully reflect or capture the core ideas of a paper (Strader, 2011). Additionally, the selection of keywords can influence the searchability of papers, and factors such as the author's attitude, background, and knowledge may affect the keywords they choose (Babaii & Taase, 2013). Furthermore, some conference papers do not provide keywords. Therefore, we decided to use a large language model to generate keywords ourselves to stand for the epistemic objects of the paper. This decision was made not only out of necessity but also as a strategic move to enhance the quality and consistency of our dataset.

Figure 1. Number of Papers in CS and AV Fields



We employed the Llama2 model (Touvron, Lavril, Izacard, Martinet, Lachaux, Lacroix et al., 2023), equipped with 7 billion parameters, to generate epistemic objects based on the abstracts of papers. Llama2 was selected for its ability to rapidly process large datasets with high accuracy, which ensures that we can extract meaningful insights from our extensive collection of academic papers without incurring additional costs, a significant advantage for large-scale research projects like ours. Moreover, previous studies have demonstrated Llama2's efficacy in extracting key features from clinical documents, achieving around 90% accuracy (Wiest, Ferber, Zhu, Van Treeck, Meyer, Juglan et al., 2023). We provided prompts to Llama2 to act as an honest, ethical, and accurate assistant for generating epistemic objects based on abstracts. An example of these detailed prompts is provided in the appendix.

Table 1. Example of Abstract and Epistemic Object Generated by Llama1	
Abstract	**Epistemic Objects Generated by Llama2**
Recent development in fully convolutional neural network enables efficient end-to-end learning of semantic segmentation. Traditionally, the convolutional classifiers are taught to learn the representative semantic features of labeled semantic objects. In this work, we propose a reverse attention network (RAN) architecture that trains the network to capture the opposite concept (i.e.,what are not associated with a target class) as well. The RAN is a three-branch network that performs the direct, reverse and reverse-attention learning processes simultaneously. Extensive experiments are conducted to show the effectiveness of the RAN in semantic segmentation. Being built upon the DeepLabv2-LargeFOV, the RAN achieves the state-of-the-art mIoU score (48.1%) for the challenging PASCAL-Context dataset. Significant performance improvements are also observed for the PASCAL-VOC, Person-Part, NYUDv2 and ADE20K datasets.	Convolutional Neural Network, Semantic Segmentation, Reverse Attention Network, Direct Attention, Inverse Concept

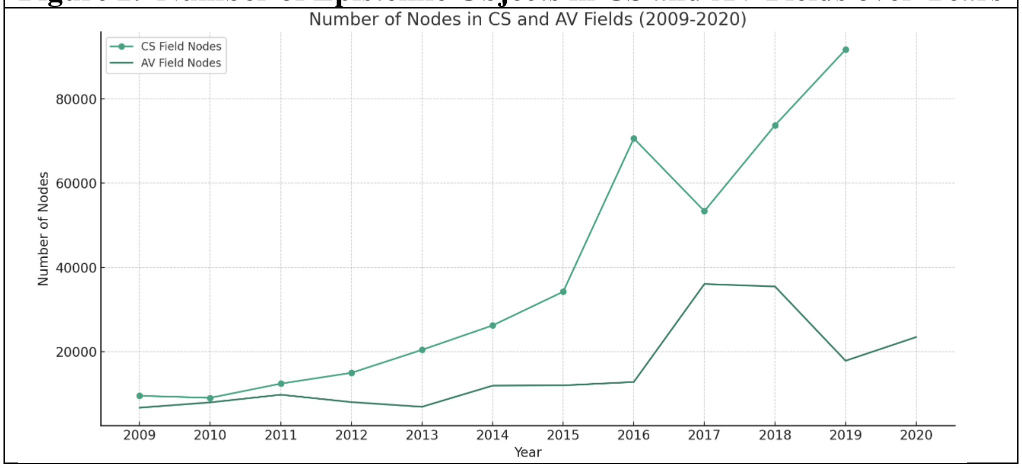
We chose abstracts as our source to generate our epistemic objects because they succinctly encapsulate the core themes and findings of a paper. Many previous studies have used abstracts for keyword extraction due to the balance they offer between efficiency and accuracy (Bhowmik, 2008; Firoozeh, Nazarenko, Alizon, & Daille, 2020; Rose, Engel, Cramer, & Cowley, 2010). This approach aligns with the established practices in academic research, where abstracts are designed to provide a concise yet comprehensive overview of a paper's content. To ensure the epistemic objects are representative, we also manually checked the performance of the Llama2 model. Table 1 shows an example of epistemic objects generated by Llama2 and the related abstract.

After epistemic object extraction, we undertook a data-cleaning process. We normalized terms to address variations, such as merging acronyms with their full forms (e.g., 'CNN' with 'convolutional neural network') and reconciled singular and plural forms (e.g., 'neural network' with 'neural networks'). After the data cleaning process, we identified a total of 416,448 epistemic objects in the CS dataset and 189,286 epistemic objects in the AV dataset.

Descriptive Statistics on Epistemic Objects

Figure 2 illustrates the annual number of epistemic objects in those two fields. The decrease in the number of nodes with the increase in the number of papers in 2017, suggests a high degree of similarity among the epistemic objects derived from these papers. This trend indicates a decreasing diversity in the subject matter of the papers.

Figure 2. Number of Epistemic Objects in CS and AV Fields over Years

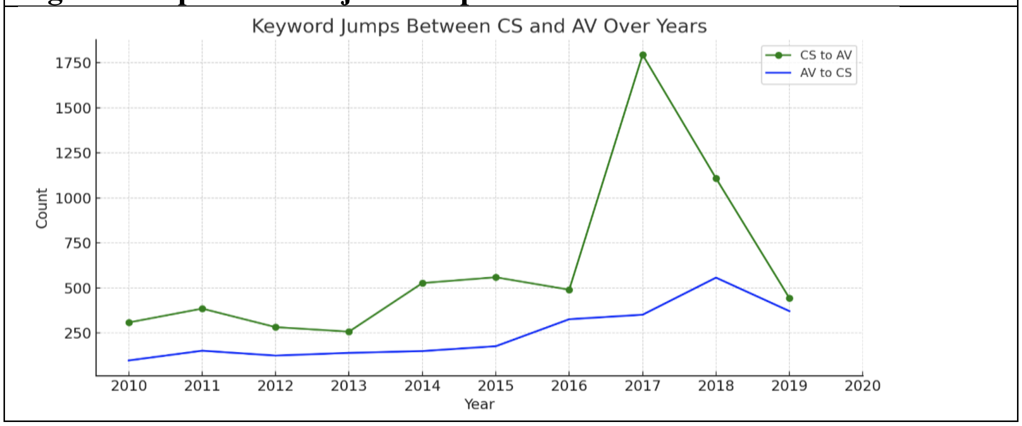


We proceeded to identify epistemic objects that were common to both the CS and AV research networks. We explored the dynamics of these epistemic objects, particularly analyzing their flow patterns. This included investigating whether they migrated from CS to AV, from AV to CS, or emerged concurrently in both fields.

Our analysis revealed a bidirectional flow of epistemic objects between the AV and CS domains. Of the 21,950 epistemic objects shared between the two, approximately 49.4% (10,839) transitioned from CS to AV. Examples of such epistemic objects include 'deep neural network', 'face recognition', 'generative adversarial network', 'sentiment analysis', and 'semi-supervised learning'. Conversely, around 40.5% (8,891) of the epistemic objects migrated from AV to CS, including terms like 'accident', 'public transport', 'attitude', 'traffic flow', and 'driver'. Notably, 2,220 epistemic objects appeared simultaneously in both fields, illustrating a concurrent emergence. Examples of these are 'stream water', 'cross classification', 'multisensor', 'moving platform', and 'neural network'.

We also observed that, on average, epistemic objects took approximately 4.03 years to transfer from CS to AV. In contrast, the reverse transfer from AV to CS averaged around 3.97 years. Figure 3 illustrates the annual trends in the number of epistemic objects transitioning between the two fields.

Figure 3. Epistemic Object Jump Between Two Fields Over Years



Variables Extracted from Networks

We constructed an epistemic object co-occurrence network across various years for both fields. In this network, nodes represent epistemic objects extracted from academic papers, while edges denote the co-occurrence relationships between these objects. This framework allows us to utilize epistemic objects as proxies for the flow of epistemic objects between fields.

Dependent variable. Our dependent variable is the event of an epistemic object 'jumping' from one field to another, which is operationalized as a binary outcome: '1' indicates that an epistemic object has appeared in the other field, whereas '0' signifies that the epistemic object remains exclusive to its field of origin.

Main variables. To measure the structural embeddedness within the network, we employ degree centrality, which is the count of connections an epistemic object has with others within the network. To measure junctional embeddedness, we utilize betweenness centrality (Grewal et al., 2006). This measure reflects an epistemic object's role as a bridge along the shortest paths between other pairs of epistemic objects within the network. It is computed as the sum of the fraction of all-pairs shortest paths that pass through the epistemic object of interest. These centrality measures serve as our primary variables.

Control variables. We controlled for the year to capture any overarching trends or effects specific to the time period. Additionally, we account for the longevity of an epistemic object in its originating field. We also controlled the random effects of epistemic objects.

Given the long-tailed distribution of our network metrics, we have applied logarithmic transformations to normalize the data distribution. Additionally, our dataset underwent standardization to mitigate the impact of disparate scales and outliers. The descriptive statistics and correlations post-standardization are detailed in Table 2, providing a comprehensive overview of our variables' behaviors and interrelations.

Table 2. Descriptive Statistics and Correlations

Variable	**Mean**	**Std**	**1**	**2**	**3**	**4**
Structural embeddedness (1)	0.00	1.00	1.00			
Junctional embeddedness (2)	0.00	1.00	0.33	1.00		
Object Age (3)	3.17	2.19	0.09	0.04	1.00	
Jump (4)	0.23	0.42	0.13	0.00	0.16	1.00

Model

We used a generalized logistic mixed-effects model to examine our hypotheses and to analyze the dynamic impact of epistemic object positions over time. We chose this model because of its ability to adeptly handle the complex nature of our panel data and we posited that distinct epistemic objects exert random effects on their jumping behavior. It can effectively manage the mixed effect inherent in our dataset where observations are nested within epistemic objects and accommodate the binary nature of our dependent variable "Jump". Its robustness against autocorrelation in longitudinal data, resilience to non-normal distributions, and capability to handle missing data enable a nuanced and reliable analysis.

Our main variables are structural embeddedness and junctional embeddedness measured by degree centrality and betweenness centrality respectively. We also included a series of year dummies to control for time-specific unobserved heterogeneity. Furthermore, we lagged the dependent variable by one year to account for the temporal delay in influence between fields and to mitigate reverse causality concerns. Specifically, we estimate:

$$Jump_{i,t+1} = \beta_0 + \beta_1 Structual\ Embeddedness_{i,t} + \beta_2 Junctional\ Embeddedness_{i,t} + \beta_3 KeywordAge_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

where i and t are indexes for epistemic object and year, respectively, μ_i indicate the random effect of epistemic objects and ν_t is the year fixed effect and $\varepsilon_{i,t}$ represents the error term. We will examine the significance and direction of β_1 and β_2 to check our first and second hypotheses.

RESULTS

To test our hypotheses, we conducted four distinct models. Model 1 includes only control variables. Model 2 examines the effect of structural embeddedness, defined as the extent to which an epistemic object is integrated within a particular knowledge domain. Model 3 centers on the role of junctional embeddedness, which refers to the connections an epistemic object has across different knowledge domains. Model 4 includes both structural and junctional embeddedness to explore their combined effects. Table 3 reports our results, focusing on epistemic objects transitioning from Computer Science (CS) to Autonomous Vehicles (AV).

Hypothesis 1 (H1) posits that the structural embeddedness of an epistemic object will positively influence its transition across knowledge boundaries. In Model 2, we observed a significant positive effect of structural embeddedness ($\beta = 0.034$, $p < 0.01$), supporting H1. However, in Model 4, the impact of structural embeddedness was positive but not significant, suggesting only partial support for H1. Hypothesis 2 (H2) posits that junctional embeddedness will positively influence this cross-boundary jump. Both Model 3 and Model 4 showed a significant and positive relationship for junctional embeddedness (Model 3: $\beta = 0.046$, $p < 0.001$; Model 4: $\beta = 0.039$, $p < 0.01$), fully supporting H2. These results indicate that the inclusion of junctional embeddedness diminishes the significance of structural embeddedness.

To validate these findings, we conducted several robustness checks. First, we used an alternative measurement of structural embeddedness that does not consider edge weight. Additionally, we employed a generalized fixed effect approach, omitting the random effect of epistemic objects. The consistency of results, with and without random effects, bolsters the credibility of our findings.

Table 3. Effect of Network Embeddedness on Objects Jumps

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Structural embeddedness	--- ---	0.03** (0.01)	--- ---	0.02 (0.01)	0.01 (0.01)
Junctional embeddedness	--- ---	--- ---	0.05*** (0.01)	0.04 ** (0.01)	0.15*** (0.04)
Structural embeddedness X	--- ---	--- ---	--- ---	--- ---	-0.04*** (0.01)

Junctional embeddedness					
Object Age	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)
Constant	-1.84 *** (0.06)	-1.85 *** (0.06)	-1.86*** (0.06)	-1.87*** (0.06)	-1.88*** (0.06)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Object Variance	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
AIC	38069.20	38063.60	38058.30	38057.20	38048.50
BIC	38182.10	38185.20	38179.90	38187.50	38187.40

*Note: Number of observations: 35,488; Number of objects: 10,839; *p<0.05, **p<0.01, ***p<0.001. Standard error in the parentheses.*

Given the mixed results regarding the impact of structural embeddedness, we recognized the need for a deeper investigation into the dynamics between structural and junctional embeddedness. The separate analyses in Models 2 and 3 highlighted the individual effects of these variables, while Model 4 integrated them to observe their combined impact. However, the nuanced findings prompted us to consider the possibility of an interaction effect, where the influence of one variable depends on the level of another. We conjecture that structural and junctional embeddedness are not merely additive but potentially synergistic or antagonistic. Consequently, we introduced Model 5 to explore the interaction effect. Model 5 exhibited lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values (AIC = 38048.5; BIC = 38187.4), suggesting that it balances model simplicity with the quality of fit, in line with Vrieze (2012). The interaction between structural and junctional embeddedness was significant (β = -0.035, p < 0.001), indicating a more complex relationship between these variables and the object transition process. Thus, structural embeddedness may dampen the positive impact of junctional embeddedness on the cross-boundary jumps.

This phenomenon may be caused by several mechanisms. First, epistemic objects with high structural embeddedness often encounter challenges like information overload and redundancy.

This can diminish their effectiveness in acting as bridges or brokers between different knowledge domains, a role that is crucial for those with high junctional embeddedness. Additionally, these epistemic objects are typically more deeply embedded within specific knowledge networks or communities, constraining their global perspective and reach, which are vital for facilitating cross-boundary knowledge transfer. Moreover, a tendency for these epistemic objects to be more aligned with intra-group connections rather than inter-group collaborations can further limit their function as bridges, thereby negatively impacting the efficiency of their transition across different knowledge domains or fields. In simpler terms, an epistemic object that is too "popular" or "specialized" in the CS domain may find it difficult to realign or reestablish itself in the AV domain.

Building on this understanding, we sought to further explore how the dynamic interplay between structural and junctional embeddedness influences the cross-boundary jumps of epistemic objects over time. This temporal dimension is critical, as the impact of embeddedness on knowledge transfer could evolve or manifest differently at various stages of an object's life cycle. By analyzing the effect over different time periods, we aim to uncover whether the interaction between structural and junctional embeddedness remains consistent, intensifies, or diminishes as epistemic objects mature and evolve in their journey from CS to AV.

To investigate this, we segmented our sample into subgroups based on the time taken for epistemic objects to transition from CS to AV. We defined these subgroups across eight distinct time intervals: $T \leq 2$ years, $T = 3$ years, $T = 4$ years, $T = 5$ years, $T = 6$ years, $T = 7$ years, and $T \geq 8$ years. We applied our established models, including the interaction term, to each of these time-based subgroups to observe potential variations in the impact of structural and junctional embeddedness across different stages of the transition process. Table 4 presents the results across these varied time periods.

Table 3. Effect of Network Embeddedness on Objects Jumps across Different Time Period							
Variable	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Time	T<=2	T=3	T=4	T=5	T=6	T=7	T>=8
Junctional embeddedness	1.01*** (0.14)	-0.41 (-0.48)	2.23*** (5.99)	3.41*** (0.50)	2.22 *** (3.68)	2.06 * (2.39)	-0.03 (-0.12)
Structural embeddedness	-1.38*** (0.07)	-0.34*** (-3.45)	-0.26*** (-5.33)	-0.09 (0.06)	-0.02 (-0.37)	-0.03 (-0.35)	0.14*** (3.52)
Structural embeddedness X Junctional embeddedness	-0.29*** (0.05)	1.22* (2.11)	-0.48*** (-4.97)	-0.98*** (0.16)	-0.56 * (-2.37)	-0.44 (-1.41)	0.00 (0.16)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observation	5858	4107	5184	5250	5598	4956	12734
Number of Objects	4027	1367	1296	1050	933	708	1458
AIC	5871	4170.8	4480.1	3721.4	3133.6	2139.9	3961.2
BIC	5971.1	4265.6	4578.4	3819.9	3233	2237.6	4073

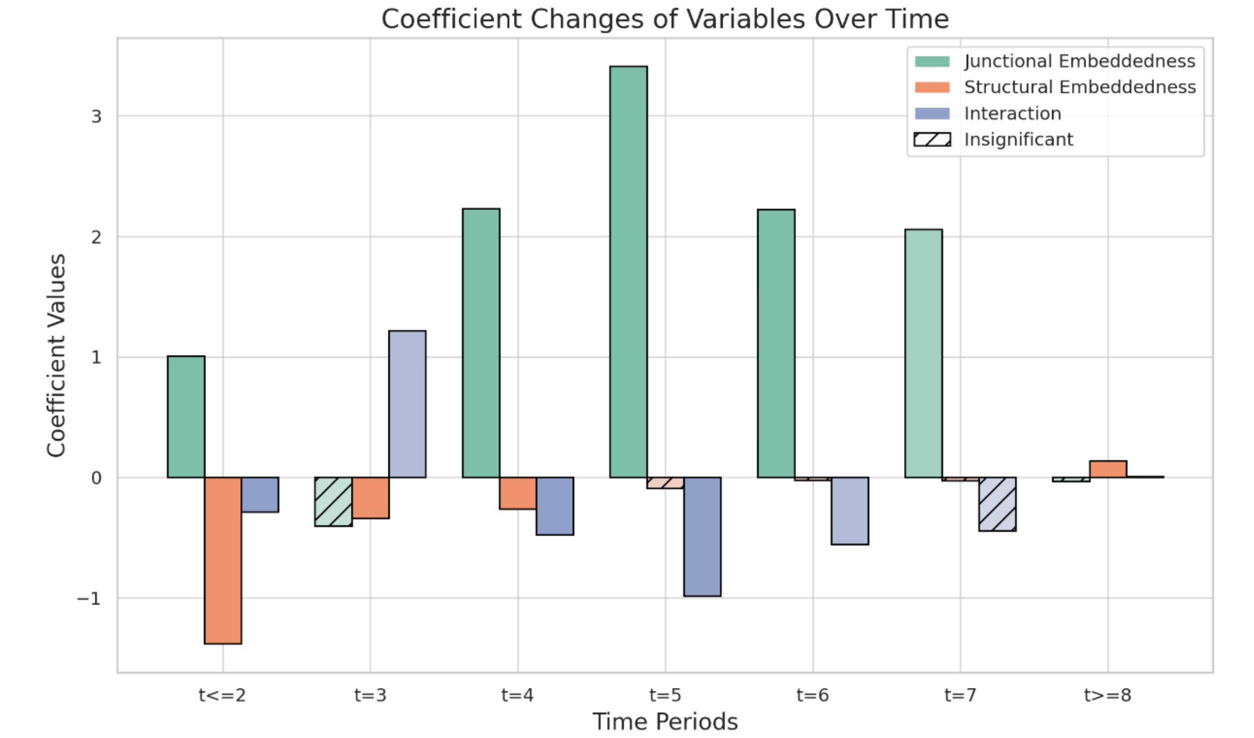
*Note: T refers to the year it takes for an object to jump into another field; *p<0.05, **p<0.01, ***p<0.001; Standard error in the parentheses.*

In the initial phase of quick jumps (T <= 2), we observe a highly significant positive effect of junctional embeddedness (β = 1.009, p < 0.001), suggesting its crucial role in facilitating the rapid transition of epistemic objects. This finding points to a strong correlation between an object's interconnectedness and its agility in migrating across fields. In contrast, structural embeddedness during this phase shows a significant negative impact (β = -1.379, p < 0.001). This indicates that an epistemic object deeply ingrained within its original field might face obstacles in transitioning quickly, possibly due to its established complexity or robustness. The interaction effect in this early stage is notably negative (β = -0.286, p < 0.001), suggesting that the combined high structural and junctional embeddedness may actually hinder the rapid transition of knowledge.

As the analysis moves into the middle phase (T = 3 to T = 7), a different pattern emerges. Junctional embeddedness displays an increasing positive effect, reaching its peak at T = 5 (β = 3.41, $p < 0.001$), and then gradually decreasing in significance by T = 7. This peak suggests an optimal point where junctional embeddedness is most conducive to facilitating transitions. Concurrently, the negative effect of structural embeddedness progressively diminishes and becomes insignificant by T = 5. This change might reflect the gradual adaptation of the epistemic object within its initial domain, making it more amenable to transitioning to other fields. Throughout this phase, the interaction effect acts consistently as a counterbalance to the effect of junctional embeddedness. Its significant negative impact throughout this period implies a complex interplay where the combined influence of high structural and junctional embeddedness regulates the transition process.

In the later phase (T >= 8), the dynamics shift again. The significance of junctional embeddedness in facilitating transitions wanes, indicating that for more extended transition periods, other factors might become more influential. On the other hand, structural embeddedness shows a slight positive effect (β = 0.139, $p < 0.001$), suggesting that over long periods, deeply embedded epistemic objects may gradually align with transition processes, possibly as they become more foundational or universally recognized within their original domain. The interaction effect, less significant in this phase, reflects a time-dependent adaptive interplay of the epistemic object across domains.

Figure 4. The Effects of Structural and Junctional Embeddedness Over Time



Overall, Figure 4 depicts a picture of the intricate and evolving interplay of structural and junctional embeddedness in the transition of epistemic objects. It highlights a dynamic landscape where junctional embeddedness initially plays a pivotal role in quick transitions but gradually becomes less significant over time. Structural embeddedness, initially a hindrance, slowly transitions to a less obstructive and potentially facilitative role. The consistent moderating influence of the interaction effect across different phases underscores a complex dynamic between these types of embeddedness throughout the transition process, revealing the multifaceted nature of knowledge dissemination and adaptation in varying academic and research contexts.

DISCUSSION

Cross-boundary Innovation as Recombinant Search in Heterogeneous Landscapes

Our study aimed to understand the dynamics of cross-boundary innovation, particularly in the context of AI, by viewing it as a recombinant search process across heterogeneous innovation landscapes. We focused on the jump of epistemic objects between the Computer Science (CS) and Autonomous Vehicle (AV) fields, conceptualizing these transitions as indicative of cross-boundary innovation.

Our findings underscore the importance of taking into account the structural attributes of epistemic objects within networks, namely their popularity and role as a bridge, in enhancing the likelihood of their transfer across different landscapes. This transition is not merely a random occurrence but is influenced by the network embeddedness of these objects in their respective networks. We observed that objects serving as network bridges are more likely to make such jumps, suggesting that their position in a network signals usefulness to innovators in other domains.

Furthermore, our exploration of interaction effects revealed a more nuanced understanding of these dynamics. The interaction between structural and junctional embeddedness suggests that the effectiveness of one type of embeddedness can be contingent on the level of the other, adding complexity to how we understand epistemic object transfer in innovation networks.

Toward a Theory of Cross-boundary AI Innovation

Digital innovation fueled by artificial intelligence demands cross-boundary jumps between heterogeneous innovation landscapes. Our current study offers an initial entry point to explore how such cross-boundary innovation can occur. At the same time, our finding further shows that we need a deeper exploration of how such innovations take place, particularly the temporality of innovation and the role of the structural position of epistemic objects.

One particularly promising avenue for further research is the temporal dimension of cross-boundary innovation. Specifically, analyzing the lagged effects will allow an understanding of how the impact of different variables may evolve or manifest differently over time. This investigation will provide deeper insights into the delayed influences that certain network attributes exert on the cross-boundary jumps of epistemic objects. Additionally, further research can delve into the movement trends of these epistemic objects within their respective networks. Investigating whether a trend towards central positions in the network influences their likelihood of transitioning to another domain will be of particular interest. This can be complemented by studying possibilities of specific movement patterns that precede or follow their jump behavior, offering a more dynamic view of these transitions.

Another fruitful direction is to explore the post-jump trajectories of epistemic objects. Not all epistemic objects that cross a boundary will likely succeed in producing meaningful innovations. Does the structural position of an object in its original network affect the post-jump position in the new network? How does the jump affect the objects' trajectory in the original network? Furthermore, in this study, we only explore the cross-boundary jumps from CS to AV. At the same time, we observed cross-boundary jumps in the opposite direction. How shall we understand the bidirectionality of the jumps?

Epistemic objects' value is not inherent. Rather, it is relational. Thus, the relationality of the epistemic objects is crucial in further understanding cross-boundary AI innovation. Specifically, Um et al. (2022) found that the relationship among epistemic objects evolves, creating dynamic inter- and intra-community patterns. Future research should assess how the location of an object, not just in the entire network but within its specific community, influences its jump likelihood. By exploring whether centrality or periphery within these smaller units has a bearing on the jumping behavior, we can gain further insights into the micro-dynamics of network influence. Moreover, the interaction effects can be explored in greater detail. This exploration will not only incorporate other network metrics and factors but will also consider the nature and strength of connections within the network. Such a detailed examination of interaction effects will enrich our understanding of the complex interplay of factors driving cross-boundary innovation.

Prior research on innovations often highlights the role of innovators (citation). In our study, we deliberately decenter the role of human actors to shed light on the role of epistemic objects (citation – Latour). However, the reputation of human actors who created these epistemic objects, their structural position in social networks, and the institution that they are affiliated with are likely to influence the cross-boundary jump of the objects. These variables will help us to gain a fuller picture of the broader ecosystem influencing these transitions, providing a more holistic understanding of the dynamics at play. These future research endeavors can expand our understanding of the intricate mechanisms driving AI innovation across different domains, contributing further to the evolving discourse in this field.

CONCLUSION

The highly malleable nature of AI allows it to be recombined in almost limitless ways across various industries. As such, the mechanism of how the knowledge about new AI technologies invented by computer scientists can be transferred to other areas of specialization warrants research. Our findings add a new perspective to the growing literature on AI innovation by examining cross-boundary AI innovation from the angle of recombinant search across heterogeneous innovation landscapes, illustrating the importance of particularly attending to AI-related epistemic objects that bridge other objects in the field, as they are more likely to be materialized into specific applications in different use contexts.

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APPENDIX

Table A1. Computer Science (CS) and Autonomous Vehicles (AV) Journal and Conference list

	CS Journal and Conference list	**AV Journal and Conference list**
1	ACM Transactions on Knowledge Discovery from Data	IEEE Transactions on Intelligent Transportation Systems
2	AI (Artificial intelligence)	Transportation Research Part C: Emerging Technologies
3	Computational Linguistics	Transportation Research Part A: Policy and Practice
4	IEEE Computational Intelligence Magazine	Transportation Research Part D: Transport and Environment
5	IEEE Transactions on Fuzzy Systems	Transportation Research Part E: Logistics and Transportation Review
6	IEEE Transactions on Neural Networks and Learning Systems	Transportation Research Part B: Methodological
7	IJCV (International Journal of Computer Vision)	Accident Analysis & Prevention
8	International Journal of Robotics Research	Transport Policy
9	JMLR (Journal of Machine Learning Research)	Journal of Transport Geography
10	Journal of Artificial Intelligence Research	IEEE Intelligent Vehicles Symposium
11	Neural computing	Journal of Air Transport Management
12	TASLP (IEEE Transactions on Audio, Speech and Language Processing)	Transportation Research Part F: Traffic Psychology and Behavior
13	TPAMI (IEEE Transactions on Pattern Analysis and Machine Intelligence)	Transportation Research Procedia
14	TR (IEEE Transactions on Robotics)	Computer-Aided Civil and Infrastructure Engineering
15	IEEE Transactions On Systems, Man And Cybernetics Part B, Cybernetics	Transport Reviews
16	Expert Systems with Applications	Transportation
17	Applied Soft Computing	IEEE Intelligent Transportation Systems Conference

18	Knowledge-Based Systems	Transportation Research Record
19	Neural Computing and Applications	IEEE Vehicular Technology Magazine
20	Neural Networks	Transportation Science
21	Engineering Applications of Artificial Intelligence	
22	AAAI(the Association for the Advance of Artificial Intelligence)	
23	ACL (The Association for Computational Linguistics)	
24	COLT (Computational Learning Theory)	
25	CVPR (IEEE Conference on Computer Vision and Pattern Recognition)	
26	ECCV (European Conference on Computer Vision)	
27	ECML (European Conference on Machine learning and knowledge)	
28	EMNLP (Conference on Empirical Methods in Natural Language Processing)	
29	ICCV (IEEE International Conference on Computer Vision)	
30	ICLR (International Conference on Learning Representations)	
31	ICML (International Conference on Machine Learning)	
32	IJCAI (International Joint Conference on Artificial Intelligence)	
33	NeurIPS (Neural Information Processing Systems)	
34	International Conference on Artificial Intelligence and Statistics	
35	Conference on Learning Theory (COLT)	
36	International Joint Conference on Neural Networks	