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Building University-Industry Co-Innovation Networks in Transnational Innovation Ecosystems: Towards a Transdisciplinary Approach of Integrating Social Sciences and Artificial Intelligence

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Abstract: This paper presents a potential solution to fill a gap in both research and practice that there are few interactions between transnational industry cooperation (TIC) and transnational university cooperation (TUC) in transnational innovation ecosystems. To strengthen the synergies between TIC and TUC for innovation, the first step is to match suitable industrial firms from two countries for collaboration through their common connections to transnational university/academic partnerships. Our proposed matching solution is based on the integration of social science theories and specific artificial intelligence (AI) techniques. While the insights of social sciences, e.g., innovation studies and social network theory, have potential to answer the question of why TIC and TUC should be looked at as synergetic entities with elaborated conceptualization, the method of machine learning, as one specific technic off AI, can help answer the question of how to realize that synergy. On the way towards a transdisciplinary approach to TIC and TUC synergy building, or creating transnational university-industry co-innovation networks, the paper takes an initial step by examining what the supports and gaps of existing studies on the topic are, and using the context of EU–China science, technology and innovation cooperation as a testbed. This is followed by the introduction of our proposed approach and our suggestions for future research.

Keywords: transnational industry cooperation; transnational university cooperation; transnational innovation ecosystem; EU–China; science, technology and innovation cooperation; transdisciplinary approach; artificial intelligence; machine learning

1. Introduction

While there is growing awareness of the role of digital technologies in transforming organizations and social relationships [1], the new economy (called platform economy or digital platform economy) based on digital technologies is changing the nature of globalization [2], in which the focus has been shifted from countries (globalization 1.0) and companies (globalization 2.0) to individuals and groups (globalization 3.0) [3]. The involvement of individuals or citizens in multi-faced social life is crucial in sustainable development [4–6] in ecological, social, and economic dimensions [7]. In this paper, we try to bring interactions of key actors in transnational innovation processes, previously mainly explored through social science approaches, into the digital domain, applying some specific artificial intelligence (AI) technologies, i.e., machine learning and knowledge representation and reasoning. Our focus is on the relations between transnational industry cooperation (TIC) and transnational university cooperation (TUC) in transnational innovation ecosystems (see more descriptions about the concept of transnational innovation ecosystem in the following section), which share basic assumptions of

sustainability and globalization 3.0. TIC is concentrated on joint research and development (R&D) and co-production; TUC is mainly concerned with academic research collaboration. The research problem of TIC and TUC synergy building, as described below, has emerged in the context of innovation studies and their adjacent fields. We try to resolve the problem by integrating relevant studies in social sciences (in the fields of innovation studies, higher education research and international relations with respect to EU and China) and AI technologies (i.e., machine learning and knowledge representation and reasoning).

The literature of innovation studies, which conceptualizes reciprocal relations and proactive interactions between universities, industry, government and citizens for promoting innovation [8,9], stresses the importance of synergy building between cross-sector organizations. Particularly, university and industry (U–I) interactions constitute a core area in innovation studies [10]. While the innovation processes are becoming globally interconnected [11–14], there is also an urgent demand to extend cross-sectoral organizational synergy building to the transnational context. For instance, it has been evidenced, though mainly in the industrial context, that technological capabilities for innovation are dispersed in international innovation networks [15] and the degree of R&D internationalization is increasing [16,17]. Thus, actors from both university and industry sectors, as key contributors to technological capabilities and R&D, are likely to become international [13].

However, academic research is far behind the needs for further integration between TIC and TUC arising from the practices of transnational STI cooperation. Although one widely shared view in innovation studies is that universities have a prominent role in the national or regional innovation system, e.g., through co-creation partnerships with industry [8,18,19], the research of U–I cooperation in transnational contexts is rare in the literature. For instance, in their literature review of U–I international knowledge transfer, Govind and Küttim [20] only found 26 articles (mainly in the fields of innovation studies and higher education research) meeting their search criteria in the Scopus and Web of Science databases. Amongst the 26 articles, U–I interactions in the transnational context are mainly seen in the form of universities from one country interacting with enterprises from another country, which is echoed in other literature e.g., [21–23]. Other studies deal with joint R&D between universities and branches of international companies e.g., [24]. The patterns of transnational U–I interactions examined in the existing literature can be illustrated in Figure 1.

When innovation systems become global [25] or internationalized [26], international university cooperation could added value to the process [27]. Some rare studies e.g., [23,28–30] do touch upon the issues of how TUC could be aligned with and supportive of broader societal priorities and development goals in transnational contexts. However, there is a lack of profound exploration in this area, particularly from theoretical and methodological perspectives.

In the context of transnational innovation networks, the interactions between TIC and TUC can be understood as synergetic entities or transnational U–I co-innovation networks (Figure 2). In such networks, new ideas and approaches from various internal and external sources are integrated in a platform to generate shared values [31]. The core elements of co-innovation include "collaboration, coordination, co-creation, convergence, and complementary" [32] (p. 361).

Figure 2 demonstrates that two industrial firms that are unfamiliar with each other, respectively from Country A and Country B, could be connected for potential collaboration by utilizing their common connections to existing university collaborations (especially individual collaborators) between the two countries. Although our focus is on how TUC can support TIC, once TIC and TUC synergetic entities are formed, the TIC would enhance the quality and value of TUC.
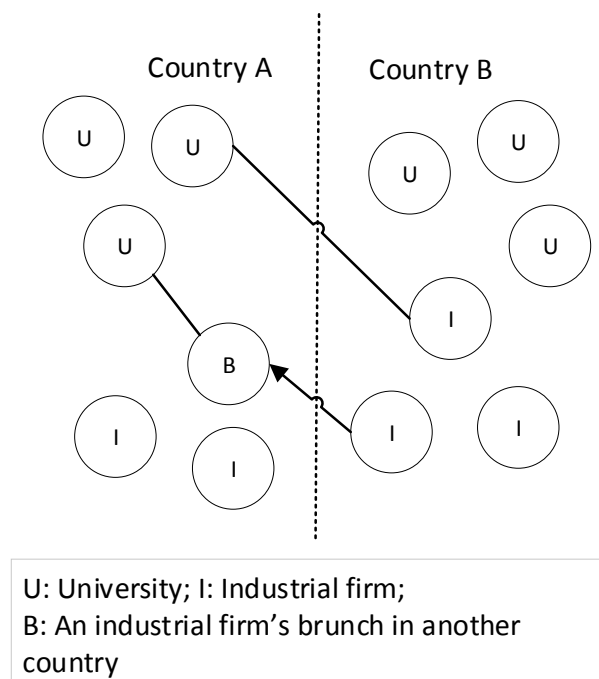
Figure 1. Examples of transnational university and industry (U–I) interactions examined in the existing literature.
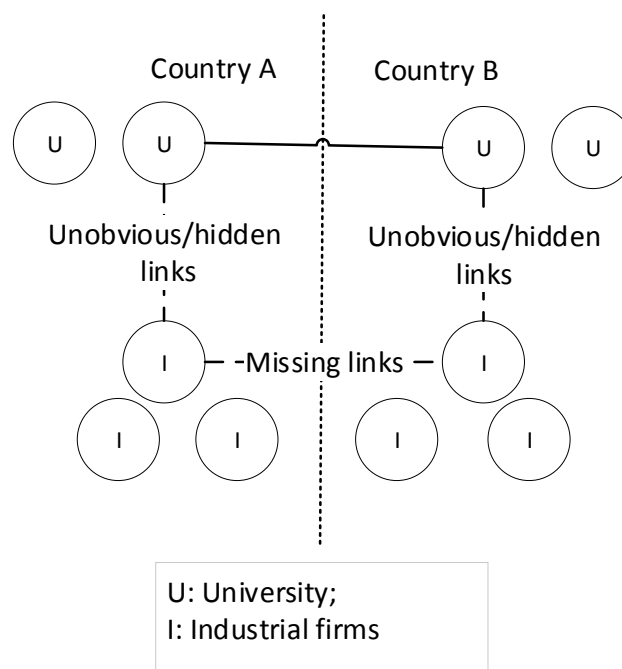

Figure 2. The transnational industry cooperation (TIC) and transnational university cooperation (TUC) synergetic entities (or transnational U–I co-innovation networks) to be tackled in our research.

Compared to existing studies on U–I interactions in transnational context (Figure 1), our investigation of U–I co-innovation networks (Figure 2) is novel in two aspects. First, although the subject of university and industry interactions in transnational context is not new in research, our study is different to existing approaches by discovering unobvious/hidden links between TUC and TIC. When links are hidden, it means that the links are unobvious or the data revealing the links are scarce or not apparent. Second, when it comes TIC, we not only look at existing collaboration of

industrial firms across countries as examined by current studies, but specifically explore how missing links between potential transnational industrial partners could be bridged through utilizing the hidden links. The dash lines in Figure 2 represent either hidden or missing links that are rarely examined in the existing studies but will be the focus of our proposed approach. Missing links demonstrate that the actors with potential for reciprocal collaboration are not connected. However, the actors can be connected by leveraging the hidden links. Third, while current research related to the topic are mainly in the field social science studies, we seek an approach integrating insights of both social sciences and AI technology.

The lack of interaction between TIC and TUC is also seen in the practices of transnational science, technology and innovation (STI) cooperation. For instance, as indicated by the first author's recent interviews of actors involved in EU–China STI cooperation, in the EU–China context, when European high-tech firms, especially small- and medium-sized enterprises (SMEs), seek Chinese counterparts for cooperation, they normally go directly to the industry sector, sometimes through business brokers. As a result, the Chinese partners that first appear to them are not necessarily the most suitable ones. This could be explained by three causes. First, the business brokers, e.g., consulting companies or governmental business promotion agencies, have a limited pool of Chinese companies as candidates to be matched with European SMEs. Second, when matching collaborators, human decisions are often subject to the "homophily principle"—a tendency in which people form ties with similar others [33]. Selecting a "friend of a friend" helps strengthen existing social clusters [33], but does not help to reach those unknown communities and individuals [34], who could potentially contribute to innovation [35]. Third, although one may notice the limitation of professional social matching based on human decisions, it is difficult to find suitable tools and data to resolve the problem [34].

Our proposition is that European and Chinese industrial firms can be best matched through their connections to existing university cooperation between both sides. In so doing, transnational U–I co-innovation networks are formed, which are crucial for enhancing the performance of EU–China STI cooperation. This has also been implied by the interviews mentioned above.

Now there is a great opportunity to exploit EU–China university cooperation to support EU–China industry cooperation, because EU–China higher education cooperation has reached an unprecedented level, demonstrated by not only a large scale of student/staff exchange but also increasingly deeper research collaboration and joint education programs [30]. For instance, there were 383 participating institutions from China in 274 projects in the EU's Seventh Framework Program (2007–2013). Although China is no longer considered to be a beneficiary country in the Horizon 2020, the Chinese Ministry of Science and Technology provides co-funding to support Chinese research organizations involved in the EU's Horizon 2020 projects. In the Web of Science database, the number of co-authored publications between Chinese and European authors has increased from 12,669 in 2011 to 35,218 in 2018.

The EU–China context is used as a testbed for three reasons. First, there is huge potential for STI cooperation between the EU and China. Second, the scales of both higher education and industry in the EU and China are tremendous, which provide abundant data for testing and application. Third, since the EU and China have different, sometimes contrasting, social structures and value systems, if we can find effective solutions to build TIC and TUC synergies in EU–China STI cooperation, the approach is likely to be applied (with possible adjustment) in other transnational contexts.

While using a specific EU–China context helps illustrate our research problem, the underlying research gaps concerning TIC and TUC synergy building are general. To narrow the gaps, we must first clearly see what the gaps are. Thus, this paper will analyze how the state-of-the-art studies have shed light on the following questions as well as limitations in answering these questions:

- Why should TIC and TUC be looked at as synergetic entities?
- How can the synergy building be theoretically elucidated?
- How can the synergy building be methodologically realized?

After that, we will present our proposed approach in brief, and discuss how it could help advance the frontier of research on the topic. It should be mentioned that the paper is primarily on the conceptual level. When it comes to our proposed AI-based approach we focus on developing operating principles rather than final technological solutions. The method in this paper is primarily based on reviewing, analyzing and synthesizing relevant literature.

2. Why Should TIC and TUC Be Looked at as Synergetic Entities?

The synergy building between TIC and TUC in the context of EU–China STI cooperation, which takes place when innovation ecosystems of both the EU and China come across (as illustrated in Figure 3). Despite our focus on the sectors of university and industry, it should be noted that the EU–China transnational innovation ecosystem consists not only of enterprises and universities but also governmental agencies and various intermediary organizations. When building the TIC and TUC co-innovation networks in the EU–China context, it is essential to discover the hidden links and bridge the missing links as show in Figure 3.
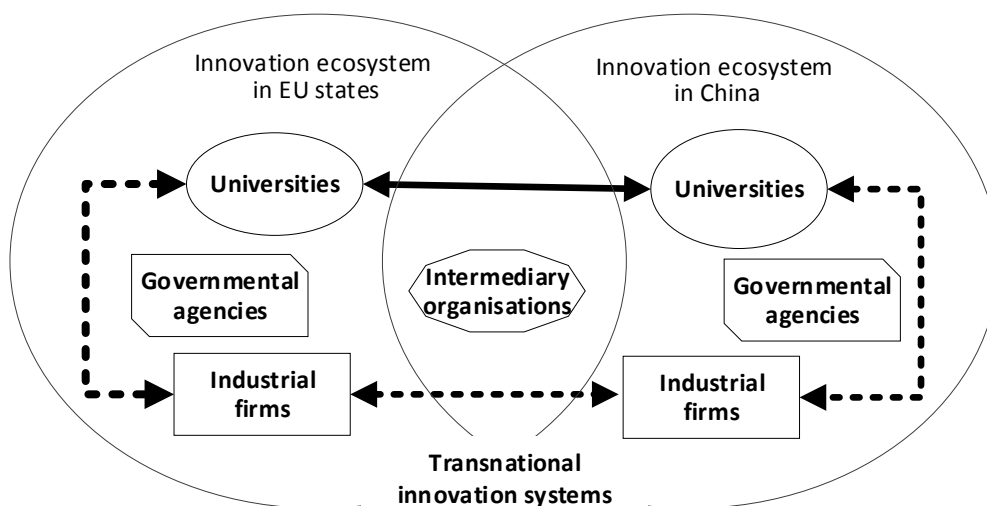

Figure 3. EU–China university cooperation and EU–China industry cooperation in the context of the EU–China transnational innovation ecosystem.

The insights of the following three research areas may provide hints on why TIC and TUC synergy building (in the EU–China context) is necessary, namely (1) the conceptualization of transnational innovation ecosystems, (2) research on universities' third mission and (3) studies on EU–China STI cooperation.

2.1. Transnational Innovation Ecosystems

Due to the increasing importance of international linkages in the knowledge-based society and a growing public awareness of the need for environmentally sustainable economic development, the term "transnational or global innovation ecosystem" has gradually become popular in both scholarly literature and policy rhetoric. While the concept of the transnational ecosystem has been applied on both the system level [36] and the sector and company levels [25], what is most relevant to the present research is the system-level literature. A transnational innovation ecosystem generally refers to the integration process between two or more innovation ecosystems across national borders with different levels of transnational integration [37,38].

To further understand the transnational innovation ecosystem, one must understand what an innovation ecosystem is. In a commonly cited definition, innovation ecosystems are regarded as "complex relationships that are formed between actors or entities whose functional goal is to enable technology development and innovation" [39] (p. 2). The innovation ecosystem shares most

of its features with the innovation system, which consists of complex functions and interactions amongst various organizations and institutions [40,41]. What is new in the innovation ecosystem is its ecological aspect, characterized by the interdependency among different collaborative actors and the co-evolution/co-creation that binds them together over time, along with the sustainable development dimension [42–44].

The literature on transnational innovation ecosystem has indicated, though implicitly, that TIC and TUC could be looked at as synergetic entities. Based on analyzing several definitions of "ecosystem", Sotarauta, Heinonen, Sorvisto, and Kolehmainen [38] suggested several key features of the innovation ecosystem, including "interconnectedness" (everything is connected to everything), "organic nature" (the system evolves through its components' continuous adaptation to changing situations) and being "multi-locational" (knowledge flows and innovation processes take place in multiple geographical locations) (pp. 31–32). All these infer that complex interactions amongst a variety of (transnational and cross-sectoral) actors shape adaptation processes in an innovation ecosystem. Such generic inferences may imply that TIC and TUC could form symbiotic relations to better adapt to increasingly complex and fast-changing environments.

Some other studies draw specific attention to the role of universities in the transnational innovation ecosystem. In a report on case studies of transnational innovation systems, Chaminade and Nielsen [36] addressed the importance of identifying already existing transnational initiatives (i.e., university and industry sectors) in forming transnational innovation systems. They suggested that available resources should support existing bottom-up transnational initiatives rather than start new ones from scratch in a top-down matter. Raunio, et al. [45] noted that "the transnational innovation infrastructures could be based more on the activities of universities or regional actors" (p. 2). They further suggested that the global university campuses could potentially help bridge the gap between the national innovation system and relevant innovation systems abroad.

2.2. Universities' Third Mission

One may intuitively assume that transnational university cooperation in the transnational innovation ecosystem is a well-studied topic. This is because of a widely shared understanding regarding the prominent role of universities in national or regional innovation systems, reflected in studies dealing with the third mission of universities [46], both in higher education research (inside-out view) e.g., [18,47–49] and innovation system studies literature (outside-in view) e.g., [8,40,41,50]. As recently stated by UNESCO's Chief of Higher Education, Peter J. Wells, "Perhaps never before in recent history has the role of higher education been so intricately tied to the economic, social, and environmental fabric of the modern world" [51] (p. 31). Since the knowledge-based society is becoming more globally interconnected, universities' societal engagement should also be conducted on a global scale.

However, most studies on transnational university cooperation are in the field of internationalization of higher education, which is primarily concerned with the teaching and research missions of universities [52,53] or with the mobility of knowledge from the perspective of human geography [54]. The studies on international graduate employability e.g., [55,56] are closest to addressing the relevance of international higher education to industry in a global context.

Nevertheless, some rare studies e.g., [23,28,29] do shed light on how transnational university cooperation could be aligned with and supportive of broader societal priorities and development goals in transnational contexts. Heide, Sijde, and Terlouw [28] explicitly explored transnational university cooperation in knowledge transfer. However, the authors solely focused on transnational research cooperation in the EU context mainly concerning types of cooperation and universities' motivations for the cooperation, and did not extend their discussion to the links of transnational university cooperation to industry sectors. Cai [30] clearly stated that China-EU higher education cooperation should be planned and developed in the broader context of Sino-EU strategic partnership building, as a call for further research.

2.3. EU–China Transnational STI Cooperation

The booming practices of EU–China STI cooperation have rarely been explored scientifically, remaining marginal in EU–China studies. The existing literature on the EU–China relationship e.g., [57–59] deals with three main pillars of cooperation between the EU and China, namely the strategic dialogue initiated in 2005, the economic and trade dialogue commenced in 2008 and the "People-to-People Dialogue" launched in 2012 to improve cooperation in education, culture, youth and research.

However, the necessity of TIC and TUC synergy building can be foreseen in the burgeoning interests of the EU and China in STI cooperation, which has been expedited by the signing of the "EU–China Innovation Cooperation Dialogue" in 2012. The Dialogue complements and ensures synergy with the "Agreement on Science and Technology Cooperation between the EU and China" in 1998. The innovation cooperation involves both industrial organizations and universities (as well as research institutes) [60]. The progress of EU–China STI cooperation in both higher education and industry is not merely a matter of quantity; its very nature is undergoing a transformation.

The nature of the EU industry's cooperation with China is changing from a conception of China as an important market and trade partner to that of an innovation partner [61,62], because China is not only the second largest economy in the world but also a powerful STI player [63]. China has overtaken the United States in terms of total number of science publications [64] and dominates a global ranking of the most-cited research papers published in the 30 most popular technology fields [65]. In such a context, EU–China industry cooperation is not confined to the business domain but expanded to the sector of knowledge generation.

In the field of higher education, EU–China university cooperation is facing increasing demands from society and stakeholders calling for universities to adapt their internationalization strategy from an emphasis on international scholarship exchange to being more responsible regarding the broader needs to develop the EU–China partnership [30]. This echoes the general trend in the internationalization of higher education in the EU, which has been increasingly influenced by the globalization of economics and societies, as well as the importance of knowledge in economic development and competition [66].

2.4. Limitations of Existing Literature

The literature on both transnational innovation ecosystems and universities' third mission has implied why synergy building between TIC and TUC is important in transnational innovation ecosystems, but the inferences are implicit and hypothetical. Both theoretical and empirical efforts on the topic are lacking. Recent studies and reports on EU–China relations indicate that the changing nature of EU–China cooperation requires synergy building between cooperation in both the university and industry sectors. However, it is surprising how little interaction exists between the two areas of cooperation on both the levels of policy-making and organizational practice. Neither has synergy been addressed in research on EU–China STI cooperation, which tends to report on cooperation separately in the university sector e.g., [67] and the industry sector e.g., [68].

3. How Can the TIC and TUC Synergy Building Be Theoretically Elucidated?

Although state-of-the-art research reflects fast-growing attention to TIC and TUC synergy building, there are no theoretical frameworks that elucidate relations amongst diverse actors in transnational innovation ecosystems. Even the concept of the innovation ecosystem exists on a high level of abstraction and is used loosely. It is often understood as a metaphor rather than as a theory or framework [42]. Oh, Phillips, Park, and Lee [42] noted that the mimetic quality of the term "innovation ecosystem" mainly appeals to the news media, demonstrating the public relations value of the term, but not its value in research. They found "few academic articles using 'innovation ecosystem' in a manner that would distinguish an innovation ecosystem from an innovation system" [42]. Along the same lines, Ritala and Almpanopoulou [69] called for future research to improve the conceptual,

theoretical and empirical rigor regarding the notion of the innovation ecosystem. Nevertheless, some other social science theories may provide useful, theoretical accounts of the mechanisms underlying the interactions between TIC and TUC, though in a direct manner, such as the Helix models of innovation, institutional theory and social network theory.

3.1. Helix Models of Innovation

Helix models of innovation, discussed here, include three concepts, namely Triple Helix Model [8], Quadruple Helix Model [9], and Triple Helix of sustainability [70]. The three concepts with different emphasis on the key dimensions innovation and societal development can supplement one another for a comprehensive understanding of the nature of contemporary society with respect to innovation.

Although the thesis of the Triple Helix Model [71] was originally developed based on empirical observations of successful regional innovation systems, its core theoretical assumptions can be applied to transnational or global contexts. Following this perspective, a transnational innovation ecosystem consists of the triple helix interactions of three functional spaces, namely transnational knowledge space, transnational innovation space and transnational consensus space [8,72]. The three spaces are respectively related to three functions, namely novelty production, normative control and wealth generation [73]. In each space, there are three overlapping spheres of transnational cooperation evolving in the respective sectors of university, industry and government, but one kind of sphere may outweigh the others. Such a Triple Helix Model of transnational innovation ecosystem is illustrated in Figure 4.
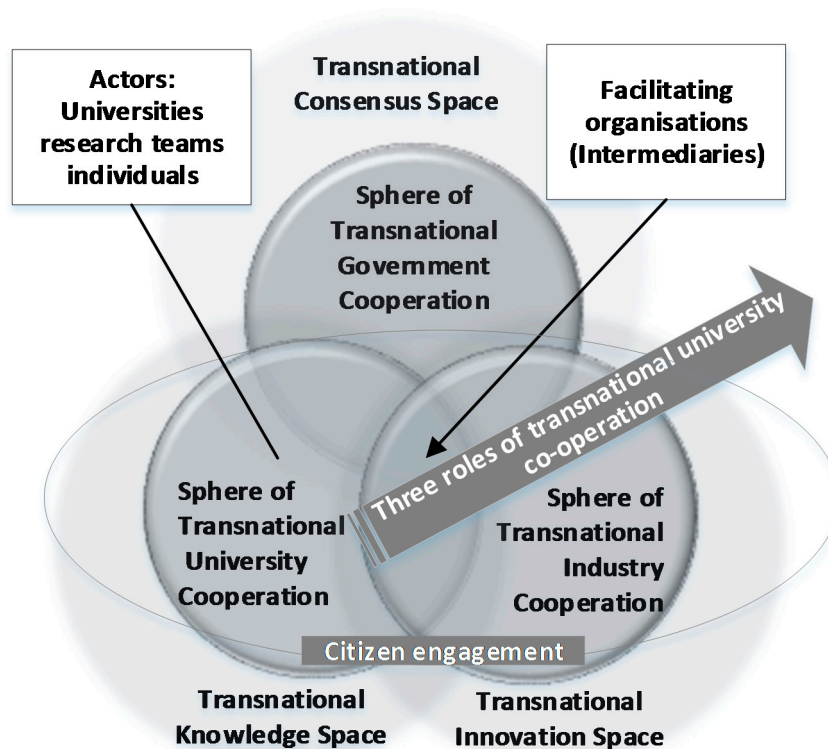

Figure 4. Triple Helix Model of the transnational innovation ecosystem.

Carayannis and Campbell [9] developed the Quadruple Helix model from the basis of the Triple Helix in order to address the "media-based and "culture-based public", "arts, artistic research and arts-based innovation" (p. 218), by adding the 'fourth helix' also called as the "civil society" [74] (p. 5). The core rationale of Quadruple Helix centers on Mode 3 knowledge production, which is developed on the basis of Mode I and Mode 2 types of knowledge production by Gibbons et al. [75], who predicted a shift in knowledge production from Mode 1 to Mode 2. Mode 1 refers to basic university research on

disciplinary basis. The Mode 2 in turn, emphasizes knowledge application, interdisciplinary research and problem solving. Mode 3 type of knowledge production is an extension for Mode 1 and 2 type of knowledge production [75]. It "allows and emphasizes the co-existence and co-evolution of different knowledge and innovation paradigms" [9] (p. 201). Mode 3 is the nexus of the emerging 21st century innovation ecosystem, where people, culture and technology meet and interact to catalyze creativity, trigger invention, and accelerate innovation across scientific and technological disciplines, public and private sectors, in a top-down, policy-driven as well as bottom-up, entrepreneurship-empowered fashion [9,76].There is a seemingly shared view about the possible extension from Triple Helix to Quadruple Helix (adding civil society as the fourth helix) [76,77]. However, we take the position that civil society is considered too important to be merely treated as an additional helix in the Quadruple Helix. Rather, it is an institutional foundation [78,79] or "a launch pad for the take-off of triple helix interactions" [72] (p. 20). Thus, citizens' engagement is positioned in Figure 4 as the foundation of transnational Triple Helix interactions. Nevertheless, we admit that the Triple Helix Model has not explicitly addressed the emerging phenomena or new characteristics in innovation ecosystems. Meanwhile, we consider that the relatively more elaborated theoretical foundations of Triple Helix Model may help enhance the explanation power of Quadruple Helix [80], which was conceptualized to cope with the innovation ecosystem of the 21st Century [6].

Moreover, Triple Helix model is needed to be further improved with the dimension of sustainable development. In this regards, Scalia, Barile, Saviano and Farioli [70] suggested the model of Triple Helix of sustainability based on both the concept of Triple Bottom Lines of Elkington [7] and the Triple Helix Model of innovation Leydesdorff and Etzkowitz [81]. It implies that interactions between society, economy and environment must be considered when studying innovation, either approached by the Triple Helix Model or Quadruple Helix Model.

The foundational statement of the Triple Helix Model is that the interactions between university, industry, and government sectors provide optimal conditions for innovation [8]. The core mechanism underlying these interactions is "taking the role of the other" [8]. Organizations taking on non-traditional roles are viewed as a major potential source of innovation. In the meantime, they still retain their traditional functions. To add the sustainability or ecosystem dimension in the Triple Helix model, the role of university must go beyond production and capitalization of knowledge [82], as main function of the third mission of universities.

In transnational contexts, the roles of transnational university cooperation are more than producing and transferring knowledge across national borders. There are two additional roles, namely fostering institutional change (concerning norms and values) in transnational innovation ecosystems and building trust between various actors in the systems [83]. The development of innovation systems is largely concerned with institutional change [40,41] and successful cooperation in research, development, and innovation relies on trust between the collaborators [84]. Both institutional change and trust building are even more salient in transnational innovation ecosystems because of the more complicated institutional configurations and distance between the collaborators in a transnational context [36]. The role of university as institutional entrepreneur [85] or social trust builder [86] is relevant to sustainable development because the it brings in social capital into the analytical foci of innovation ecosystem [6], in addition to human and financial capital as emphasizes of the concept of university's "third mission". The two roles concerning institutional change and trust building can be respectively explained by institutional logics theory and social network theory.

3.2. Institutional Theory

From the perspective of institutional theory, there are two essential issues in forming an innovation (eco)system, namely institutional conditions enabling innovation [78] and the agency of actors to change the institutional context [87,88]. These two factors can be respectively explained by the institutional logics approach and the notion of institutional entrepreneurship.

Institutional logic is defined as "a set of material practices and symbolic constructions" that constitute an institutional order's "organizing principle" and are "available to organizations and individuals to elaborate" [89] (p. 248). The institutional logics approach helps better explain how institutions both enable and constrain action by incorporating macro structure, local culture and human agency [90]. One central pervasive argument of the institutional logics perspective is that multiple and contending logics provide the dynamic for potential change in both organizations and societies [90].

The notion of institutional entrepreneurship, which was originally introduced by DiMaggio [91] as a way to reintroduce actors' agency into institutional analysis, refers to the activities of institutional entrepreneurs, who not only initiate diverse changes in the institutional environment but also actively participate in the implementation of such changes [92]. Institutional entrepreneurs may initiate institutional change intentionally or unintentionally. They may have a high or low social status and "can be organizations or groups of organizations, or individuals or groups of individuals" [92] (p. 68). Leca, et al. [93] reported that institutional entrepreneurship is likely to take place in contexts with conflicting institutional arrangements. Battilana, Leca and Boxenbaum [94] stated that "joint actions and interactions between institutional entrepreneurs" (p. 77) provide conditions conducive to institutional entrepreneurship.

In the Triple Helix Model, for instance, there is mingling of the logics of state, market/corporate and profession, which respectively dominate in the spheres of government, industry, and academia [94]. In transnational contexts, the institutional configurations would be more complex. According to the institutional logics perspective, crossing organizational field operations, e.g., between the fields of university and industry, is likely to generate novelty [95]. The multiple and sometimes hybrid institutional environments, created by triple helix interactions, also forester institutional entrepreneurs.

3.3. Social Network Theory

The social network theory could provide useful hints regarding where and how actors crossing sectors and national borders can be connected or can collaborate for synergy building. For instance, in his seminal work titled *Strength of Weak Ties*, Granovetter [96] contends that in the case of job hunting, what is most helpful for the job seekers is not strong ties within their dense networks of relatives and friends for social support. Rather, it is the connections derived from weak ties, composed of distant acquaintances, which give access to new (not redundant) information and job offers. In other words, the strength of weak ties lies in its nature of being a source of novel information. Burt [97] put forward that social networks, especially in their function of facilitating weak ties that bridge dense networks, reflect the effect of "social capital" [98]. Instead of using the concept of "weak tie", Burt [99] coined the concept of the "structural hole". A structural hole refers to a lack of connection between two nodes (e.g., two individuals who have complementary sources of information), and social capital can be best realized through the brokerage of that structural hole. The underlying assumption is:

> Opinion and behavior are more homogeneous within than between groups, so people connected across groups are more familiar with alternative ways of thinking and behaving. Brokerage across the structural holes between groups provides a vision of options otherwise unseen, which is the mechanism by which brokerage becomes social capital. [100] (p. 349)

When applying social network theory in the context of innovation, it has been suggested that stimulating innovation within networks requires a combination of both strong and weak ties [101–103]. "Weak ties aid exploration (the generation of new ideas), whereas strong ties aid exploitation (the implementation of new ideas)" [35] (p. 212). The creation and diffusion of innovation are mostly attributed to weak ties [104]. For instance, one reason why the Triple Helix Model [8,71] provides optimal conditions for innovation is because through the interactions of university, industry and government—three traditionally not overly connected sectors or networks—a large variety of new ideas and technologies are likely to be created.

Trustworthy social relationships and common institutional frameworks are also beneficial for interactive learning and innovation [105]. While the most useful knowledge/ideas would come from weak ties, one challenge is that the trust between actors connected by weak ties might be low. The trust issue is even more important when the knowledge is tacit. Increasing the level of trust is crucial to enhancing the performance of weak ties in knowledge transfer [106].

3.4. Limitations of Existing Literature

The literature on the Helix models of innovation [8,9,70,71], institutional logics [90] and social network theory [96,97] may somewhat explain the mechanisms underlying the interactions between TIC and TUC from the perspectives of overlapping roles, institutional change and trustworthy relationship building. However, there is still a big gap regarding comprehensively theorizing the synergy building between TIC and TUC. Specific limitations of these theories are outlined below.

First, the theories focus on relations between obvious actors, and are not designed to identify and analyze unobvious or hidden relations. For instance, while the role of brokers in the innovation process has been strongly indicated by the social network theory and evidenced in empirical studies, the challenge in practice is how to proactively identify them. Sometimes, even potential brokers might not be aware of their position and potential for network building.

Second, social network theory tends to consider single nodes (either individuals or organizations) as brokers and there is no attempt to think of brokers in other formats. It excludes the assumption that a pair of nodes, e.g., in the form of a transnational university research partnership, together could play the role of filling structural holes.

Third, the current theoretical accounts about university and industry relations address the domestic context and need to be adjusted for analyzing phenomena in transnational innovation ecosystems.

4. How Can the TIC and TUC Synergy Building Be Methodologically Realized?

Although TIC and TUC synergy building is a new topic in research, some popular approaches in social and computer sciences can provide methodological bases for empirical exploration on how to build synergies between TIC and TUC, including identifying potential collaborators and building relations. These approaches are social network analysis, professional social matching and AI.

4.1. Social Network Analysis

Social network analysis (SNA) are the methods and techniques (primarily relying on computer-based statistical measures and link analysis algorithms) used for discovering patterns of interaction between social actors in social networks. Tabassum, et al. [107] have identified different types of SNA.

Traditional SNA includes statistical measures of social networks. The fundamental units in this analysis are vertices and edges. Vertices (or nodes) can refer to a wide variety of individual entities, such as people and organizations or publications, and an edge connects a pair of vertices that represent numerous kinds of (direct or indirect) relationships (such as communication, cooperation, friendship, and trade) between individual entities.

More recent SNA focuses on node identification and link prediction. Node identification is used to identify the most valuable or influential nodes in certain network settings. To support this kind of analysis, several link analysis algorithms are devised, amongst which the most popular ones are the HITS29 and Brin and Page [108] algorithms. Parallel to node identification is the analysis of link prediction, which predicts which links are more likely to appear in the future. More specifically, such SNA is used for predicting re-occurring links instead of new links [107]. Both node identification and link prediction are important approaches in synergy building between TIC and TUC.

The other two emerging SNA approaches deal with, respectively, community detection and evolving networks, which are useful for TIC and TIC synergy building. The former is concerned with communities in networks and the latter emphasizes networks that are generated in real time, which are

not static but evolving [107]. The core of TIC and TUC synergy building is concerned with relations between two communities in a transnational innovation network. The evolving aspect is especially relevant to analyzing networks in an innovation ecosystem.

4.2. Professional Social Matching

Related to SNA, a recent approach to support human collaboration is social matching, which identifies and facilitates new social connections between people using computational techniques [109]. Professional social matching (PSM) matches individuals or groups for professional collaboration and co-creation of value. It covers a range of "organizational activities, including recruitment, headhunting, community building, and team formation within or across organizations as well as individually driven activities like mentoring, seeking advisory relationships, and general networking" [34].

Olsson, Huhtamäki, and Kärkkäinen [34] compared conventional PSM based on human decisions and the computational approach of PSM. It has been suggested by knowledge management studies that the most fruitful collaboration and the capacity for high innovation may result from complementary viewpoints amongst a diverse groups of actors [110]. Thus, the traditional approach of PSM may constrain such co-creative potential, because people tend to choose collaborators with similar mind-sets and professional experiences, as well as from a limited pool of candidates. The computational approach of PSM, however, can help identify optimal collaborators with supplementary capacities and bring them together for co-creation networks. However, the existing approaches are often too simplistic [34].

Olsson, Huhtamäki, and Kärkkäinen [34] also proposed that a more advanced PSM system to be developed in the future should focus on the following dimensions when matching collaborators:

- Identifying optimal combinations of human characteristics and professional aims in certain professional activities (i.e., matching qualities and goals).
- Recommending partners for co-creative purposes, such as for business partnerships or mentoring relationships (i.e., matching individuals).
- Optimizing team formations for a project (i.e., matching multiple actors).
- Identifying suitably complementary actors for networked value creation (i.e., matching at ecosystem level).
- Balancing the supply and demand in the job market by suggesting dedicated trainings or new job openings (i.e., matching on societal level).

4.3. Artificial Intelligence: Machine Learning (ML) and Knowledge Representation and Reasoning (KR and R)

AI applications have been in use for at least 30 years in the medical and industrial contexts, but the use of AI in the social sciences is a current trend. In a social context, AI could provide useful tools for discovering new social phenomena and for testing existing theories. The basis for such AI systems can be found in the computational graph theory, which was proven to work well in computer networks [111].

Many AI-based methodologies have been put forward to construct models based on mobility patterns and predict the behavior of people individually or as a group [112,113]. These include stochastic models such as Markov Models MM) [114] and Bayesian Networks (BN), as well as non-stochastic models such as Artificial Neural Networks (ANN) and Decision Trees (DT) [115]. While researchers have used ML techniques such as ANN and DT [116], the stochastic models are preferred over these due to the uncertainty in or unpredictability of human behavior [116]. In several studies e.g., [115,116] researchers have also used Bayesian Networks.

ML and KR and R are two major techniques of AI that have the potential to provide solutions to matching transnational industrial partners through their connections to transnational academic partnerships. While humans learn things by using their brains, in ML algorithms are used by computers and robots to learn automatically (without explicit instructions) [117]. ML algorithms are based on training data, a kind of sample data. Data mining, as a field of study within ML learning, "is one

of the most effective alternatives to extract knowledge from the great volume of data, discovering hidden relationships, patterns and generating rules to predict and correlate data" [118] (p. 687). Such a technique has often been applied in social network analysis [119,120].

KR and R [121] focuses on implementing knowledge repositories built by semantic descriptions that can be interpreted by both humans and machines. There are many KR and R formalisms used to implement semantic models, such as ontologies, databases and semantic rules. The former formalism is getting attraction in several fields, such as in the industrial automation field [122,123], needing to build semantic models including information from different and interrelated concepts. One of the major benefits of using such technic is the possibility of adding a layer of reasoning in order to discover implicit knowledge from the explicit data graphs that are fed to the model. Further, ML and KR and R can be integrated to work on different layers of implementation, i.e., using them for different processing data format, syntax and semantics.

4.4. Limitations of Existing Approaches

While the three approaches supported by cutting-edge computational and computer technologies are useful for social network analysis and matching optimal collaborators, none of them can be directly used to match TIC and TUC in transnational innovation ecosystems for three reasons. First, although the recent development of social network analysis has shifted attention to node identification and link prediction, which are essential in TIC and TUC synergy building, the related methods are still lacking efficiency especially in discovering hidden links and bridging missing links as well as processing unstructured data as the focus our research [107]. Second, while computational professional social matching has been more effectively used in practice [34], it is rarely used in cross-sectoral and transnational contexts. Third, while AI benefits business life, technology and industry [124], it is rare to see any efforts placed in using AI to facilitate understandings of the social system in which industrial businesses and technological innovations are embedded. A particular challenge in the case of TIC and TUC synergy building is finding both suitable algorithms and training data.

5. Our Proposed Future Solution

To further explore the three research questions, we aim to develop a transdisciplinary approach of integrating social sciences studies and AI technology. While achieving such an ambitious goal will be a long process, we will present our preliminary thoughts about the approach here.

5.1. A Transdisciplinary Approach

Our proposed transdisciplinary approach integrates the following disciplines and/or research fields: transnational innovation ecosystems, universities' societal engagement, international relations (EU and China), Helix models of innovation, institutional theory, social network theory, social network analysis, professional social matching, ML, and KR and R. Our long-term goal is to design an AI-based system that can predict and match potential university and industry collaborators in transnational contexts, particularly matching European industrial firms with potential Chinese partner firms through their common connections to EU–China university cooperation, as demonstrated in the first two layers of boxes in Figure 5. The users of the system will be European SMEs. The users are expected to input their own professional network, including their collaborations with European university actors, on a voluntary basis, to the system to keep the database growing. Meanwhile the system will reward the users with suggested optimal industrial partners from China as well as the information concerning U–I co-innovation networks in between. Behind the user interface is the ML-based matching system. Along the lines in the second layer box, the dark grey rectangular boxes indicate examples of open data sources, used for ML.
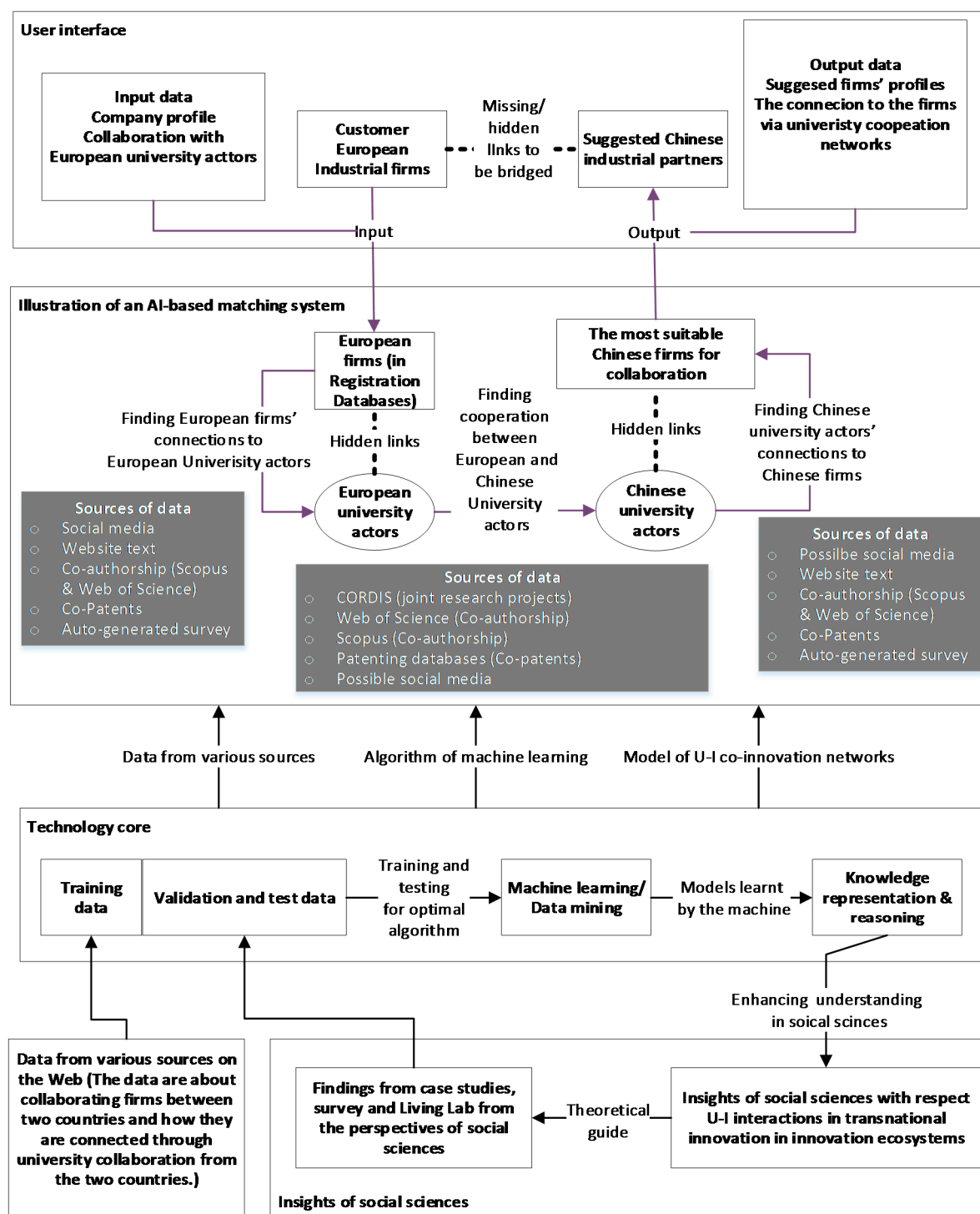
Figure 5. Illustration of an artificial intelligence (AI)-based system for building transnational university and industry (U–I) co-innovation networks.

The core technologies are ML and KR and R (demonstrated in the third layer boxes in Figure 5). To train the computer to make autonomous prediction, training data from various sources, such as those examples in the grey boxes, will be gathered. Here the data are about existing links between TIC and TUC.

The integration of social sciences and AI is shown in the third- and fourth-layer boxes in Figure 5. The insights of social sciences theories and studies, as mentioned early in the paper, will be used for guiding empirical research on TIC and TUC synergy building. The possible methods are case studies,

Living Lab and survey. The findings (data) of the research will be the sources of validation and test data, which is important for improving and optimizing the ML algorithm. On the other hand, the models developed by the AI system will help enhance understandings of TIC and TUC interactions in social science studies.

While Figure 5 illustrates an overall view of our approach, we try to give a bit more details of the AI-based methods (or the technology core in the third layer box). Our modelling and prediction of TIC and TUC co-innovation networks are on the organizational level, though our data mining will process the data of individual organizational members. Our proposed approach is composed of three phases: (1) Data Preparation, (2) Data Analysis, and (3) TIC and TUC matching. The latter is the step wherein, based on the reasoning of semantic information, the hidden cooperation links are inferred. This section describes each phase in order to provide understanding on the interrelated techniques and parts of the approach, which is depicted in Figure 6.
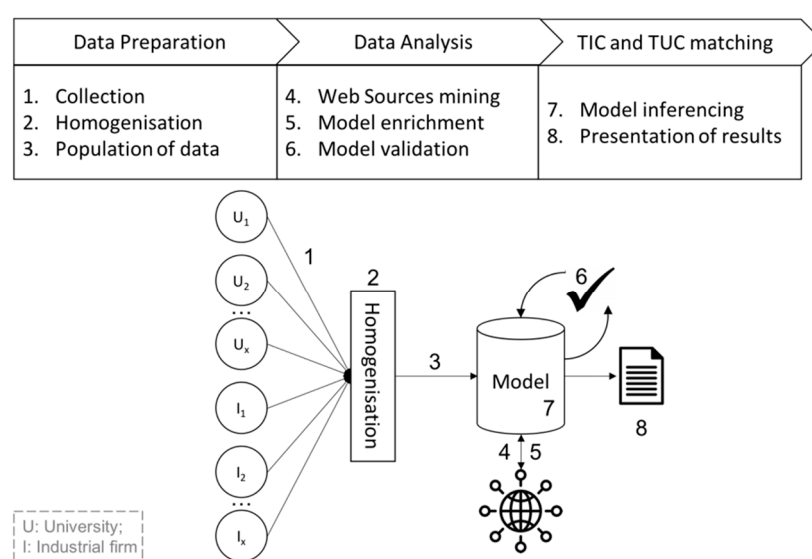

Figure 6. Different phases of the approach for inferencing transnational industry cooperation (TIC) and transnational university cooperation (TUC) matching.

Data Preparation is the first step in understanding the data and transforming it into interpretable information. In fact, data preparation is divided into three subtasks: collection, homogenization and population of data. First, the data are collected from both open source data and different partners who are willing to cooperate within the network on a voluntary basis. To achieve this, future partners will have access to a platform wherein they can fill out profile information. This information includes aspects such as name and type of organization, interests, availability of human resources and so on. Additionally, existing databases (e.g., the CORDIS EU project databases, Web of Science) and other web resources, such as provided website links and social media, are also added for further data mining. ML-based techniques will be used to mine data from web links, aiming to finding patterns that can be later used to match information to other partners in the network. Second, the data are homogenized in the platform format, which in turn is compatible with the semantic model to be populated. In this context, as the semantic model is built within ontologies, the selected format is the Ontology Web Language (OWL), which can be queried by other parts of the platform within SPARQL Protocol and RDF Query Language (SPARQL) queries. On top of the OWL statement, the model includes a set of semantic rules that derive from inferences at the third stage of the proposed approach.

Once the data are prepared and thus included in the semantic model, the data are analyzed in the Data Analysis phase. There are two types of analysis in this phase. First, as stated previously, web sources are mined in order to find common patterns. Found patterns permit the creation of new

statements that will extend the ontology. Furthermore, the semantic model consistency is validated within a semantic reasoner. In this approach, the Pellet reasoner is used for such a validation.

Finally, once the model is populated and validated, the third stage regards finding the potential cooperation between parties within the TIC and TUC matching phase. This is achieved within the inference of ontological descriptions enriched within semantic rules. More precisely, Semantic Web Rule Language (SWRL) rules are used, as they are compatible with Resource Description Framework (RDF)-based models and hence OWL ontologies. The finding of implicit relations between ontological resources within similar interaction of technologies and languages have been demonstrated on previous research work by the authors [125,126].

One of the benefits of this approach is that the described stages are automatically executed with only the need for the profiles of university and industry actors. The platform engines manage the tasks regarding the corresponding data and present the results, i.e., the potential cooperation, to the collaborative partnerships. This is provided to the platform owner as a report to be later shared with the platform users.

5.2. Potential to Answer the Research Questions Using the Transdisciplinary Approach

Once our proposed approach has been developed, it will better answer the three research questions raised at the outset of the paper. To make clear how our approach advances state-of-the-art research, we contrast the potential contributions of our proposed approach to the research questions and the limitations of existing literature (Table 1).

Table 1. Answers to research questions by existing literature and our proposed approach.

Research Questions	Limitations of Existing Literature	Potential Contributions Offered by Our Proposed Approach
Why should TIC and TUC be looked at as synergetic entities?	The synergies between TIC and TUC are hypothetical. Scarce data are available for empirical exploration.	A large scale of transnational U–I co-innovation networks will be detected and developed. This will enable deep empirical investigations and even big data analyses.
How can the synergy building be theoretically elucidated?	The theories, to varying extents, elucidate the mechanisms underlying the synergy building between obvious actors crossing sectors/communities, but mainly in a domestic context. The relations between the actors are one to one (or one to more).	The AI algorithms will be based on integrating several social science theories, which provide theoretical foundations concerning developing collaborative relations (networks) between unobvious (cross-sectoral) actors in a transnational context. Our frameworks address the relations between different pairs of collaborators.
How can the synergy building be methodologically realized?	SNA: lacks efficiency in exploring hidden/missing links. Professional social matching (PSM): not for matching in a cross-sectoral and transnational context. AI technologies: no suitable algorithms and training data ready to use.	A comprehensive method will be developed by integrating social science studies and AI in the context of transnational innovation ecosystems. It is not only for detecting potential collaborators and links between them, but also for building the networks.

6. Conclusions

This paper has demonstrated how social sciences and AI could be integrated to develop a transdisciplinary approach to TIC and TUC synergy building, thus contributing to the knowledge pool in which studies on TIC and TUC have been separately reported in spite of a growing awareness on necessary of synergy building between TIC and TUC. Specifically, the originality of our research lies in four aspects.

First, while the research on TIC and TUC synergy building is almost an uncharted field, our research maps a landscape of the research area with identification of specific research gaps through extensive analysis of relevant literature. Our efforts are around discussions on how existing research

may offer useful insights and have limits in answering three questions: Why should TIC and TUC be looked at as synergetic entities? How can the synergy building be theoretically elucidated? How can the synergy building be methodologically realized? The diagnose of advantages and weaknesses of state-of-the-art research in the field not only serves as clear point of departure of our research on TIC and TUC synergy building, but also helps guide more scholars to plunge into the field.

Second, we propose a transdisciplinary approach to TIC and TUC synergy building by integrating insights of social sciences, such as Helix Model of innovation, institutional theory and social network theory, and AI, such as ML and KR and R. While the insights from social sciences have the potential to answer the question of why TIC and TUC should be regarded as synergetic entities, AI technologies can help answer the question of how such synergies can be realized. Current methods using AI (i.e., ML) in social science research tend towards two extremes: they are used either for verifying assumptions about human intelligence or for independent prediction, thus tending to replace human intelligence. We try to integrate between social-science-based theoretical modelling and data-based computational modelling, particularly regarding the understanding of TIC–TUC interactions. Empirical findings guided by social sciences theories will help improve ML algorithm by providing validation and test data. The models learnt by machine will be useful input for advancing understanding of TIC and TUC synergy building in social sciences studies.

Third, our proposed approach will specifically identify/predict hidden/missing connections between actors in TIC and TUC co-innovation networks by analyzing unstructured data from various sources, such as public databases (e.g., research projects, co-publications, patents), website text (on cooperation activities) and auto-generated survey data. In doing so, on one hand we try to advance current social network analyses, which mainly map out anticipated networks by processing classified data [107]. On the other hand, we will open new horizons for studies on professional social matching [34] from both cross-sectoral and transnational perspectives.

Finally, our approach of AI-based matching system will help realize the potential role of university for institutional change and trust building, which are important to the sustainable dimension of innovation ecosystem development.

Nevertheless, our paper is primarily on the conceptual level discussions. Despite promising potential of our approach, it must be first tested and verified with sample data. This will be our next research task. It should also be noted that matching TIC and TUC, e.g., in the EU and China context, is just the first step to building EU–China transnational co-innovation networks. To achieve full synergy of the networks, there are also other important issues that need to be deeply explored, such as research and innovation policies, entrepreneurship, knowledge management, intellectual property rights, and inter-cultural communications. This will indeed open a new area of multidisciplinary research. Studying the TIC and TUC synergy building in the EU and China context also propels an urgent demand for closer communication between two separate research communities, namely international researchers and Chinese researchers both conducting research on the topic [127].

References

1. Nambisan, S.; Wright, M.; Feldman, M. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Res. Policy* **2019**, *48*, 103773. [CrossRef]
2. Kenney, M.; Zysman, J. The Rise of the Platform Economy. *Issues Sci. Technol.* **2016**, *32*, 61–69.
3. Friedman, T.L. *The World is Flat: The Globalized World in the Twenty-First Century*; Updated and Expanded: Penguin: London, UK, 2007.
4. Barr, S. Strategies for sustainability: Citizens and responsible environmental behaviour. *Area* **2003**, *35*, 227–240. [CrossRef]
5. Kostoska, O.; Kocarev, L. A Novel ICT Framework for Sustainable Development Goals. *Sustainability* **2019**, *11*, 31. [CrossRef]
6. Carayannis, E.G.; Grigoroudis, E.; Campbell, D.F.J.; Meissner, D.; Stamati, D. The ecosystem as helix: An exploratory theory-building study of regional co-opetitive entrepreneurial ecosystems as Quadruple/Quintuple Helix Innovation Models. *RD Manag.* **2018**, *48*, 148–162. [CrossRef]
7. Elkington, J. Partnerships from cannibals with forks: The triple bottom line of 21st-century business. *Environ. Qual. Manag.* **1998**, *8*, 37–51. [CrossRef]
8. Etzkowitz, H. *The Triple Helix: University-Industry-Government Innovation in Action*; Routledge: New York, NY, USA; London, UK, 2008; 164p.
9. Carayannis, E.G.; Campbell, D.F.J. "Mode 3" and "Quadruple helix": Toward a 21st century fractal innovation ecosystem. *Int. J. Technol. Manag.* **2009**, *46*, 201–234. [CrossRef]
10. Perkmann, M.; Tartari, V.; McKelvey, M.; Autio, E.; Broström, A.; D'Este, P.; Fini, R.; Geuna, A.; Grimaldi, R.; Hughes, A.; et al. Academic engagement and commercialisation: A review of the literature on university–industry relations. *Res. Policy* **2013**, *42*, 423–442. [CrossRef]
11. Necoechea-Mondragón, H.; Pineda-Domínguez, D.; Pérez-Reveles, L.; Soto-Flores, R. Critical factors for participation in global innovation networks. Empirical evidence from the Mexican nanotechnology sector. *Technol. Forecast. Soc. Chang.* **2017**, *114*, 293–312. [CrossRef]
12. Liu, J.; Chaminade, C.; Asheim, B. The Geography and Structure of Global Innovation Networks: A Knowledge Base Perspective. *Eur. Plan. Stud.* **2013**, *21*, 1456–1473. [CrossRef]
13. Barnard, H.; Chaminade, C. Global Innovation Networks: Towards a taxonomy. *CIRCLE Work. Pap. 2011*, 1–45.
14. Pandey, N.; Desai, P.N. Exploring 'Global Innovation Networks' in Bio clusters: A Case of Genome Valley in Hyderabad, INDIA. *J. Scientometr. Res.* **2017**, *6*, 23–35. [CrossRef]
15. Zander, I. How do you mean 'global'? An empirical investigation of innovation networks in the multinational corporation. *Res. Policy* **1999**, *28*, 195–213. [CrossRef]
16. Boutellier, R.; Gassmann, O.; von Zedtwitz, M. *Managing Global Innovation: Uncovering the Secrets of Future Competitiveness*; Springer: Berlin/Heidelberg, Germany, 2008.
17. Filippaios, F.; Papanastassiou, M.; Pearce, R.; Rama, R. New forms of organisation and R&D internationalisation among the world's 100 largest food and beverages multinationals. *Res. Policy* **2009**, *38*, 1032–1043. [CrossRef]
18. Charles, D. Universities as key knowledge infrastructures in regional innovation systems. *Innov. Eur. J. Soc. Sci. Res.* **2006**, *19*, 117–130. [CrossRef]
19. Kenney, M.; Mowery, D.C. *Public Universities and Regional Growth: Insights From the University of California*; Stanford University Press: Palo Alto, CA, USA, 2014.
20. Govind, M.; Küttim, M. International Knowledge Transfer from University to Industry: A Systematic Literature Review. *Res. Econ. Bus. Cent. East. Eur.* **2016**, *8*, 5–25.
21. Albuquerque, E.D.M.E.; Britto, G.; Camargo, O.S.; Kruss, G. Global interactions between frims and universiteis: Global innovation networks as first steps towards a global innovation system. In *Texto Para Discussão N° 419*; Cedeplar, Universidade Federal de Minas Gerais: Belo Horizonte, Brazil, 2011.
22. Kalantaridis, C.; Küttim, M.; Govind, M.; Sousa, C. How to commercialise university-generated knowledge internationally? A comparative analysis of contingent institutional conditions. *Technol. Forecast. Soc. Chang.* **2017**, *123*, 35–44. [CrossRef]
23. Kauppinen, I. Towards transnational academic capitalism. *High. Educ.* **2012**, *64*, 543–556. [CrossRef]

24. Ma, J. *Internationalization of Collaborative Research Units in Chinese Flagship Research Universities: An Academic Perspective on Cross-Border Tiple Helix Linkages*; University of Hong Kong: Hong Kong, China, 2015.

25. Fransman, M.; Bogdanowicz, M. *Models of Innovation in Global ICT Firms: The Emerging Global Innovation Ecosystem*; Publications Office of the European Union: Luxembourg, 2014.

26. Carlsson, B. Internationalization of innovation systems: A survey of the literature. *Res. Policy* **2006**, *35*, 56–67. [CrossRef]

27. Cai, Y.; Jin-Kuusirinne, T. *The Role that Finnish Universities Have in a Globalising Economy*; Helsinki Times: Finland, 23 January 2014.

28. Heide, S.V.D.; Sijde, P.V.D.; Terlouw, C. Exploring 'Transnational' University Cooperation in Knowledge Transfer:A European Perspective. *Ind. High. Educ.* **2010**, *24*, 17–27. [CrossRef]

29. EU. *Report on the Outcomes of the Public Consultation on Transnational Research Cooperation and Knowledge Transfer Between Public Research Organisations and Industry, M1/FM-DD D(2006)*; EU: Brussels, Belgium, 2006.

30. Cai, Y. China-Europe Higher Education Cooperation: Opportunities and Challenges. *Front. Educ. China* **2019**, *14*, 167–179. [CrossRef]

31. Lee, S.M.; Olson, D.L.; Trimi, S. Co-innovation: Convergenomics, collaboration and co-creation for organizational values. *Manag. Decis.* **2012**, *50*, 817–831. [CrossRef]

32. Saragih, H.S.; Tan, J.D. Co-innovation: A review and conceptual framework. *Int. J. Bus. Innov. Res.* **2018**, *17*, 361–377. [CrossRef]

33. Kossinets, G.; Watts, D.J. Origins of Homophily in an Evolving Social Network. *Am. J. Sociol.* **2009**, *115*, 405–450. [CrossRef]

34. Olsson, T.; Huhtamäki, J.; Kärkkäinen, H. Directions for Professional Social Matching. *Commun. ACM* **2019**, forthcoming.

35. Barrie, J.; Zawdie, G.; João, E. Assessing the role of triple helix system intermediaries in nurturing an industrial biotechnology innovation network. *J. Clean. Prod.* **2019**, *214*, 209–223. [CrossRef]

36. Frenkel, A.; Maital, S. *Mapping National Innovation Ecosystems: Foundations for Policy Consensus*; Edward Elgar Publishing: Cheltenham, UK, 2014.

37. Chaminade, C.; Nielsen, H. *Transnational Innovation Systems*; Eclac: Santiago de chile, Chile, 2011.

38. Sotarauta, M.; Heinonen, T.; Sorvisto, P.; Kolehmainen, J. *Innovation Ecosystems, Competences and Leadership: Human Spare Parts and Venture Finance Ecosystems Under Scrutiny*; Tekes—The Finnish Funding Agency for Innovation: Helsinki, Finland, 2016.

39. Jackson, D. *What is an Innovation Ecosystem?* National Science Foundation: Arlington, VA, USA, 2011.

40. Edquist, C. *Systems of Innovation: Technologies, Institutions and Organizations*; Printer: London, UK, 1997.

41. Lundvall, B.Å. *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*; Pinter Publishers: London, UK; New York, NY, USA, 1992; 342p.

42. Oh, D.S.; Phillips, F.; Park, S.; Lee, E. Innovation ecosystems: A critical examination. *Technovation* **2016**, *54*, 1–6. [CrossRef]

43. Smorodinskaya, N.; Russell, M.G.; Katukov, D.; Still, K. Innovation Ecosystems vs. Innovation Systems in Terms of Collaboration and Co-creation of Value. In Proceedings of the 50th Hawaii International Conference on System Sciences, Waikoloa, HI, USA, 4–7 January 2017.

44. Walrave, B.; Talmar, M.; Podoynitsyna, K.S.; Romme, A.G.L.; Verbong, G.P.J. A multi-level perspective on innovation ecosystems for path-breaking innovation. *Technol. Forecast. Soc. Chang.* **2017**, *136*, 103–113. [CrossRef]

45. Raunio, M.; Kautonen, M.; Saarinen, J.P. *Models for International Innovation Policy: Transnational Channels and Regional Platforms*; TaSTI, University of Tampere: Tampere, Finland, 2013.

46. Etzkowitz, H. Academic-industry relations: A sociological paradigm for economic development. In *Evolutionary Economics and Chaos Theory: New Directions in Technology Studies*; Leydesdorff, L., van de Besselaar, P., Eds.; Printer: London, UK, 1994; pp. 139–151.

47. Benneworth, P.; Pinheiro, R.; Sánchez-Barrioluengo, M. One size does not fit all! New perspectives on the university in the social knowledge economy. *Sci. Public Policy* **2016**, *43*, 731–735. [CrossRef]

48. Clark, B.R. *Creating Entrepreneurial Universities: Organizational Pathways of Transformation*; IAU: Pergamon, Turkey, 1998.

49. Cai, Y.; Liu, C. The roles of universities in fostering knowledge-intensive clusters in Chinese regional innovation systems. *Sci. Public Policy* **2015**, *42*, 15–29. [CrossRef]

50. Fagerberg, J.; Martin, B.R.; Andersen, E.S. *Innovation Studies: Evolution and Future Challenges*; Oxford University Press: Oxford, UK, 2013.

51. Wells, P.J. UNESCO'S Introduction: The role of Higher Education Institutions today. In *Higher Education in the World 6. Towards a Socially Responsible University: Balancing the Global with the Local*; Grau, F.X., Goddard, J., Hall, B.L., Hazelkorn, E., Tandon, R., Eds.; Global University Network for Innovation (GUNi): Girona, Spain, 2017.

52. Mihut, G.; Altbach, P.G.; de Wit, H. *Understanding Global Higher Education: Insights From Key Global Publications*; SensePublishers: Rotterdam, The Netherlands, 2017.

53. Knight, J. The changing landscape of higher education internationalisation—For better or worse? *Perspect. Policy Pract. High. Educ.* **2013**, *17*, 84–90. [CrossRef]

54. Waters, J.L.; Leung, M. Trans-knowledge? Geography, Mobility and Knowledge in Transnational Education. In *Mobilities of Knowledge*; Jöns, H., Meusburger, P., Heffernan, M., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 269–285. [CrossRef]

55. Cai, Y. *Understanding Employers' Perceptions of International Graduates: An Investigation of the Employment Prospects of Finnish-Educated Chinese Graduates in Finnish Companies Operating in China*; Tampere University Press: Tampere, Finland, 2012.

56. Coelen, R.; Gribble, C. *Internationalization and Employability in Higher Education*; Taylor & Francis: Abingdon, UK, 2019.

57. Cihelková, E.; Nguyen, H.P.; Wożniaková, M.; Straková, R. The EU-China comprehensive strategic partnership in context of EU general concept of the strategic partnership. *J. Secur. Sustain. Issues* **2017**, *6*. [CrossRef]

58. Zhou, H. *China-EU Relations: Reassesing the China-EU Comprehensive Strategic Partnership*; Springer & Social Sciences Academic Press: Basel, Switzerland, 2017.

59. Brown, K. *China and the EU in Context: Insights for Business and Investors*; Palgrave Macmillan: Basingstoke, UK, 2014.

60. EU. *1st EU-China Innovation Cooperation Dialogue: Joint Statement*; Commission, E., Ed.; EU: Brussels, Belgium, 2013.

61. EUCCC. *European Business in China—Business Confidence Survey*; European Union Chamber of Commerce in China: Beijing, China, 2017.

62. EU. *Roadmap for EU-China S&T Cooperation*; European Commission: Brussels, Belgium, 2016.

63. Zhou, P.; Leydesdorff, L. The emergence of China as a leading nation in science. *Res. Policy* **2006**, *35*, 83–104. [CrossRef]

64. Tollefson, J. China declared world's largest producer of scientific articles. *Nature* **2018**, *553*, 390. [CrossRef]

65. Okoshi, Y. China's Research Papers Lead the World in Cutting-Edge Tech. Available online: https://asia.nikkei.com/Business/China-tech/China-s-research-papers-lead-the-world-in-cutting-edge-tech (accessed on 5 May 2019).

66. Hans de Wit, F.H.; Howard, L.; Egron-Polak, E. *Internationalisation of Higher Education*; European Commission: Brussels, Belgium, 2015.

67. Fan, C.; Christmann-Budian, S.; Seus, S. *Research and Innovation Cooperation Between the European Union and China*; European Commission: Brussels, Belgium, 2014.

68. García-Herrero, A.; Kwok, K.C.; Liu, X.D.; Tim, S.; Zhang, Y.S. *EU–China Economic Relations to 2025 Building a Common Future*; The Royal Institute of International Affairs: London, UK, 2017.

69. Ritala, P.; Almpanopoulou, A. In defense of 'eco' in innovation ecosystem. *Technovation* **2017**, *60–61*, 39–42. [CrossRef]

70. Scalia, M.; Barile, S.; Saviano, M.; Farioli, F. Governance for sustainability: A triple-helix model. *Sustain. Sci.* **2018**, *13*, 1235–1244. [CrossRef]

71. Etzkowitz, H.; Leydesdorff, L. The Triple Helix—University-Industry-Government Relations: A Laboratory for Knowledge-Based Economic Development. *EASST Rev.* **1995**, *14*, 14–19.

72. Etzkowitz, H. Making a humanities town: Knowledge-infused clusters, civic entrepreneurship and civil society in local innovation systems. *Triple Helix* **2014**, *2*, 1. [CrossRef]

73. Ivanova, I.A.; Leydesdorff, L. Rotational symmetry and the transformation of innovation systems in a Triple Helix of university–industry–government relations. *Technol. Forecast. Soc. Chang.* **2014**, *86*, 143–156. [CrossRef]

74. Carayannis, E.G.; Campbell, D.F.J. Quadruple and Quintuple Helix Innovation Systems and Mode 3 Knowledge Production. In *Handbook of Cyber-Development, Cyber-Democracy and Cyber-Defense*; Carayannis, E.G., Campbell, D.F.J., Efthymiopoulos, M.P., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 1–19. [CrossRef]

75. Gibbons, M.; Limoges, C.; Nowotny, H.S.S.; Scott, P.; Trow, M. The New Production of Knowledge. In *The Dynamics of Science and Research in Contemporary Societies*; Sage: London, UK, 1994.

76. Carayannis, E.G.; Campbell, D.J. Mode 3 Knowledge Production in Quadruple Helix Innovation Systems. In *Mode 3 Knowledge Production in Quadruple Helix Innovation Systems*; Springer: New York, NY, USA, 2012; Volume 7, pp. 1–63.

77. McAdam, M.; Debackere, K. Beyond 'triple helix' toward 'quadruple helix' models in regional innovation systems: Implications for theory and practice. *RD Manag.* **2018**, *48*, 3–6. [CrossRef]

78. Cai, Y. What contextual factors shape "innovation in innovation"?—Integration of insights of the Triple Helix and the institutional logics perspective. *Soc. Sci. Inf.* **2015**, *54*, 299–326. [CrossRef]

79. Cai, Y. Implementing the Triple Helix model in a non-Western context: An institutional logics perspective. *Triple Helix* **2014**, *1*, 1–20. [CrossRef]

80. Cai, Y.; Lattu, A. Civically grounded Triple Helix: Synergies between Triple Helix and Quadruple Helix models of innovation. In Proceedings of the XVII International Triple Helix Conference, Cape Town, South Africa, 9–11 September 2019.

81. Leydesdorff, L.; Etzkowitz, H. The Triple Helix as a model for innovation studies. *Sci. Public Policy* **1998**, *25*, 195–203.

82. Carayannis, E.G.; Grigoroudis, E.; Campbell, D.F.J.; Meissner, D.; Stamati, D. 'Mode 3' universities and academic firms: Thinking beyond the box trans-disciplinarity and nonlinear innovation dynamics within coopetitive entrepreneurial ecosystems. *Int. J. Technol. Manag.* **2018**, *77*, 145–185. [CrossRef]

83. Cai, Y. Towards a socially responsible entrepreneurial university: Conceptual and analytical framework building. *SPIRAL* **2018**, *2018*, 1–4.

84. Bidault, F. *Managing Joint Innovation: How to Balance Trust and Control in Strategic Alliances*; Palgrave Macmillan: Basingstoke, UK, 2012.

85. Cai, Y.; Liu, C. The Role of University as Institutional Entrepreneur in Regional Innovation System: Towards an Analytical Framework. In *Examining the Role of Entrepreneurial Universities in Regional Development*; Preto, M.T., Daniel, A., Teixeira, A., Eds.; IGI Global: Hershey, PA, USA, Forthcoming.

86. Huang, J.; van den Brink, H.M.; Groot, W. College Education and Social Trust: An Evidence-Based Study on the Causal Mechanisms. *Soc Indic Res* **2011**, *104*, 287–310. [CrossRef]

87. Sotarauta, M. An actor-centric bottom-up view of institutions: Combinatorial knowledge dynamics through the eyes of institutional entrepreneurs and institutional navigators. *Environ. Plan. C Politics Space* **2017**, *35*, 584–599. [CrossRef]

88. Kukk, P.; Moors, E.H.M.; Hekkert, M.P. Institutional power play in innovation systems: The case of Herceptin. *Res. Policy* **2016**, *45*, 1558–1569. [CrossRef]

89. Friedland, R.; Alford, R.R. Bringing society back in: Symbols, practices and institutional contradictions. In *The New Institutionalism in Organizational Analysis*; Powell, W.W., DiMaggio, P., Eds.; University of Chicago Press: Chicago, IL, USA, 1991; pp. 232–263.

90. Thornton, P.H.; Ocasio, W.; Lounsbury, M. *The Institutional Logics Perspective: A New Approach to CULture, Structure and Process*; Oxford University Press: Oxford, UK, 2012.

91. DiMaggio, P.J. Interest and agency in institutional theory. In *Institutional Patterns and Organizations: Culture and Environment*; Zucker, L.G., Ed.; Ballinger: Cambridge, MA, USA, 1988; pp. 3–21.

92. Battilana, J.; Leca, B.; Boxenbaum, E. How Actors Change Institutions: Towards a Theory of Institutional Entrepreneurship. *Acad. Manag. Ann.* **2009**, *3*, 65–107. [CrossRef]

93. Leca, B.; Battilana, J.; Boxenbaum, E. Agency and Institutions: A Review of Institutional Entrepreneurship. *Harv. Bus. Sch. Work. Pap.* **2008**, *08–96*, 1–52.

94. Liu, C.; Cai, Y. Triple Helix Model and Institutional Logics in Shenzhen Special Economic Zone. *Sci. Public Policy* **2018**, *45*, 221–231. [CrossRef]

95. Perkmann, M.; Phillips, N. Leveraging institutional distance: Institutional arbitrage in university-industry relations. In Proceedings of the New Institutionalism 7th Workshop, Lyon, France, 17–18 March 2011.

96. Granovetter, M.S. The Strength of Weak Ties. *Am. J. Sociol.* **1973**, *78*, 1360–1380. [CrossRef]

97. Burt, R.S. The Network Structure Of Social Capital. *Res. Organ. Behav.* **2000**, *22*, 345–423. [CrossRef]

98. Bourdieu, P.; Wacquant, L.J.D. *An Invitation to Reflexive Sociology*; University of Chicago Press: Chicago, IL, USA, 1992.

99. Burt, R.S. The Social Capital of Structural Holes. Ronald S. Burt, 2001, pending copyright transfer to the Russell Sage Foundation. This is a pre-print of a chapter. In *New Directions in Economic Sociology*; Guillén, M.F., Collins, R., England, P., Meyer, M., Eds.; Russell Sage Foundation: New York, NY, USA, 2001.

100. Burt, R.S. Structural Holes and Good Ideas. *Am. J. Sociol.* **2004**, *110*, 349–399. [CrossRef]

101. Abrahamson, E.; Rosenkopf, L. Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation. *Organ. Sci.* **1997**, *8*, 289–309. [CrossRef]

102. Capaldo, A. Network structure and innovation: The leveraging of a dual network as a distinctive relational capability. *Strateg. Manag. J.* **2007**, *28*, 585–608. [CrossRef]

103. Michelfelder, I.; Kratzer, J. Why and How Combining Strong and Weak Ties within a Single Interorganizational R&D Collaboration Outperforms Other Collaboration Structures. *J. Prod. Innov. Manag.* **2013**, *30*, 1159–1177. [CrossRef]

104. Gretzinger, S.; Hinz, H.; Matiaske, W. Strong Ties, Weak Ties and the Management of Innovation: The Case of Danish and German SMEs. In *New Developments in the Theory of Networks: Franchising, Alliances and Cooperatives*; Tuunanen, M., Windsperger, J., Cliquet, G., Hendrikse, G., Eds.; Physica-Verlag HD: Heidelberg, Germany, 2011; pp. 277–298. [CrossRef]

105. Boschma, R. Proximity and Innovation: A Critical Assessment. *Reg. Stud.* **2005**, *39*, 61–74. [CrossRef]

106. Levin, D.Z.; Cross, R. The Strength of Weak Ties You Can Trust: The Mediating Role of Trust in Effective Knowledge Transfer. *Manag. Sci.* **2004**, *50*, 1477–1490. [CrossRef]

107. Tabassum, S.; Pereira, F.S.F.; Fernandes, S.; Gama, J. Social network analysis: An overview. *Wiley Interdiscip. Rev.-Data Min. Knowl. Discov.* **2018**, *8*, 21. [CrossRef]

108. Brin, S.; Page, L. Reprint of: The anatomy of a large-scale hypertextual web search engine. *Comput. Netw.* **2012**, *56*, 3825–3833. [CrossRef]

109. Terveen, L.; McDonald, D.W. Social matching: A framework and research agenda. *ACM Trans. Comput. Hum. Interact.* **2005**, *12*, 401–434. [CrossRef]

110. Mitchell, R.; Nicholas, S. Knowledge Creation in Groups: The Value of Cognitive Diversity, Transactive Memory, and Open-mindedness Norms. *Electron. J. Knowl. Manag. Account. Res.* **2006**, *4*, 67–74.

111. Rangaswamy, K.D.; Gurusamy, M. Application of Graph Theory Concepts in Computer Networks and its Suitability for the Resource Provisioning Issues in Cloud Computing-A Review. *J. Comput. Sci.* **2018**, *14*, 163–172. [CrossRef]

112. Mathew, W.; Raposo, R.; Martins, B. Predicting future locations with hidden Markov models. In Proceedings of Proceedings of the 2012 ACM Conference on Ubiquitous Computing, Pittsburgh, PA, USA, 5–8 September 2012; pp. 911–918.

113. Asahara, A.; Maruyama, K.; Sato, A.; Seto, K. Pedestrian-movement prediction based on mixed Markov-chain model. In Proceedings of Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, Chicago, IL, USA, 1–4 November 2011; pp. 25–33.

114. Gambs, S.; Killijian, M.O.; Cortez, M.N.D.P. Next Place Prediction Using Mobility Markov Chains. In Proceedings of the First Workshop on Measurement, Privacy and Mobility, Bern, Switzerland, 10 April 2012; pp. 3:1–3:6.

115. Kim, B.; Kang, S.; Ha, J.Y.; Song, J. Agatha: Predicting daily activities from place visit history for activity-aware mobile services in smart cities. *Int. J. Distrib. Sen. Netw.* **2015**, *11*. [CrossRef]

116. Etter, V.; Kafsi, M.; Kazemi, E.; Grossglauser, M.; Thiran, P. Where to go from here? Mobility prediction from instantaneous information. *Pervasive Mob. Comput.* **2013**, *9*, 784–797. [CrossRef]

117. Bishop, C.M. *Pattern Recognition and Machine Learning*; Springer: New York, NY, USA, 2006.

118. Galvao, N.D.; Marin, H.D. Data mining: A literature review. *Acta Paul. Enferm.* **2009**, *22*, 686–690. [CrossRef]

119. Memon, N. *Data Mining for Social Network Data*; Springer: New York, NY, USA; London, UK, 2010.

120. Cuomo, S.; Maiorano, F. Social network data analysis and mining applications for the Internet of Data. *Concurr. Comput. Pract. Exp.* **2018**, *30*, 9. [CrossRef]

121. Brachman, R.; Levesque, H. *Knowledge Representation and Reasoning*; Morgan Kaufmann Publishers Inc.: Burington, MA, USA, 2004; p. 381.

122. Ramis, B.; Gonzalez, L.; Iarovyi, S.; Lobov, A.; Lastra, J.L.M.; Vyatkin, V.; Dai, W. Knowledge-based web service integration for industrial automation. In Proceedings of the 2014 12th IEEE International Conference on Industrial Informatics (INDIN), Porto Alegre, Brazil, 27–30 July 2014; pp. 733–739.

123. Ferrer, B.R.; Mohammed, W.M.; Lobov, A.; Galera, A.M.; Lastra, J.L.M. Including human tasks as semantic resources in manufacturing ontology models. In Proceedings of the IECON 2017 43rd Annual Conference of the IEEE Industrial Electronics Society, Beijing, China, 29 October–1 November 2017; pp. 3466–3473.

124. Makridakis, S. The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures* **2017**, *90*, 46–60. [CrossRef]

125. Ferrer, B.R.; Ahmad, B.; Lobov, A.; Vera, D.A.; Lastra, J.L.M.; Harrison, R. An approach for knowledge-driven product, process and resource mappings for assembly automation. In Proceedings of the 2015 IEEE International Conference on Automation Science and Engineering (CASE), Gothenburg, Sweden, 24–28 August 2015; pp. 1104–1109.

126. Ahmad, M.; Ferrer, B.R.; Ahmad, B.; Vera, D.; Martinez Lastra, J.L.; Harrison, R. Knowledge-based PPR modelling for assembly automation. *CIRP J. Manuf. Sci. Technol.* **2018**, *21*, 33–46. [CrossRef]

127. Chen, A.; Patton, D.; Kenney, M. University technology transfer in China: A literature review and taxonomy. *J. Technol. Transf.* **2016**, *41*, 891–929. [CrossRef]