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Proximity and impact of university-industry collaborations. A topic detection analysis of impact reports

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A R T I C L E I N F O

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A B S T R A C T

The probability to initiate university-industry collaborations (UICs), their intensity and quality, are influenced by the proximity between the collaboration partners. However, little is known about the relationship between collaborators' proximity and impact of UICs. Building on an original database of 415 UICs in the United Kingdom, we analyse the association between collaborators' proximity and the extent to which UICs generate economic, social and knowledge impact. We find that geographical and institutional proximity are substitutes in relation to economic impact, cognitive and institutional proximity are substitutes in relation to knowledge impact, and social impact is associated with cognitive and institutional distance.

1. Introduction

Increasingly competitive marketplaces, the shortening of product and technology lifecycles, and the growing complexity of innovation processes have increased industry's reliance on academic expertise (Brusoni et al., 2001; Iacobucci and Perugini, 2023). University-industry collaborations (UICs) are a frequently used mechanism to combine universities' general and disembodied knowledge with industry's applied knowledge (Wirsich et al., 2016; De Silva and Rossi, 2018; Fassio et al., 2019; Rossi et al., 2022), resulting in valuable innovations (Lee and Bozeman, 2005; Siebdrat et al., 2014; Chesbrough et al., 2018). The benefits of UICs also extend beyond the collaborators, generating economic benefits (George et al., 2002; Bozeman et al., 2013; Aksoy et al., 2022), and addressing societal challenges (Geuna and Martin, 2003; Bornmann, 2013; de Silva et al., 2019). Literature has shown that proximity between university and industry partners affects a variety of outcomes, such as the *probability to initiate* UICs, their *frequency*, and the *quality* of their research outputs. Yet, limited attention has been paid to the effects of proximity on the extent to which UICs generate *different types of impacts*.

The broader organisational literature has also addressed the effects of proximity on collaborations between organisations (not including universities), with a small number of papers focusing on the role of proximity in enhancing outcomes, or impact (Dolfsma and van der Eijk, 2016; Hung et al., 2021; Santamaria et al., 2021). However, most of this literature focuses on the proximity between individuals, often within the same organisation or cluster (Rodan and Galunic, 2004; Dolfsma and van der Eijk, 2016;). It is acknowledged that the interactions between the proximities of individuals and the proximities of the organisation they work for are complex, and that more studies are required (Mahdad et al., 2020; Steinmo and Lauvås, 2022). The findings from studies of proximity between individuals or other non-academic organisations cannot be easily extended to universities and businesses, which are widely different in terms of culture, objectives and strategies (Bertello et al., 2022). Furthermore, papers that analyse the effect of proximity between organisations tend to focus on general performance outcomes, such as innovativeness and expected benefits from knowledge exchange, without differentiating between types of impacts (Giuliani and Bell, 2005; Ozcan and Eisenhardt, 2009), and especially neglecting social impacts (Siemieniako et al., 2021).

There is, therefore, a knowledge gap about the relationship between the proximity of university and industry, and the different types of impacts of collaboration. The UIC literature has called for more research into whether different types of proximity influence specific types of innovation outcomes (Steinmo and Lauvås, 2022) for example the propensity to generate publications and innovations (Perkmann and Walsh,

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2007; Boardman and Bozeman, 2015; Ankrah and Al-Tabbaa, 2015).

This paper investigates how different facets of proximity between UIC partners, are associated with different types of impact. We propose an original conceptual framework modelling the relationships between the geographical, cognitive and institutional proximity of the collaboration partners, and the UIC's knowledge, economic, and social impacts. We build on Bozeman's (2000) model of knowledge transfer, and on the literature on proximity and the economics of knowledge (Asheim and Gertler, 2005; Asheim and Coenen, 2005), which has found that different types of proximity matter for the exchange of different types of knowledge (Davids and Frenken, 2018). We argue that the latter are associated with the generation of different types of impacts through UICs. We develop hypotheses associating different types of proximity to different types of impact of UICs, and we test them empirically using an evidence base combining: (i) reports describing the impact of 415 UICs funded by the United Kingdom's innovation agency, and (ii) additional data about UIC partners available from public sources. We further validate our findings through several in-depth interviews with selected UIC participants.

Our paper makes theoretical, methodological and practical contributions. Theoretically, our findings advance literature on UICs, by addressing the association between proximity and impact in a unique context that requires attention due to vast differences between universities and businesses (Bertello et al., 2022). Our findings also add value to interorganisational literature which, when discussing proximity, has predominantly focused on innovation performance, knowledge exchange, and commercialisability of outputs (Giuliani and Bell, 2005; Ozcan and Eisenhardt, 2009; Dolfsma and van der Eijk, 2016; Aksoy et al., 2022), rather than knowledge, economic and social impacts.

Methodologically, we propose an original approach to operationalise variables, using secondary documental sources, to capture different types of impact of UICs. We apply topic detection techniques to 415 reports describing the impact of UICs funded under the Knowledge Transfer Partnership (KTP) scheme in the UK; we then create variables, to be used in inferential analysis, associating each document to the types of impact detected through text mining. The use of text mining in innovation research is an area of growing interest (Hannigan et al., 2019; Xu et al., 2021). There have been attempts to analyse textual data in order to identify different types of impact, either through manual coding (Backhaus et al., 2017; Hughes et al., 2017) or text mining techniques (such as Latent Semantic Analysis: Kwon et al., 2017; Coussement et al., 2017). Other studies have used text-mining-based measures in inferential analysis (for example, Woltmann and Alkaersig, 2018; de Silva et al., 2021a, 2021b). In this paper we combine the two approaches, developing text-mining-based measures of impact to be used in a regression model.

Our study can help universities, their industry partners and policymakers to better strategise the nature of their interactions so as to generate intended impacts. A strategic approach to UICs is especially important since proximity may have not only positive but also negative effects on collaboration outcomes, such as innovation performance (Boschma, 2005; Dolfsma and van der Eijk, 2016; Liang and Liu, 2018).

2. Theoretical framework

2.1. Proximity between UIC partners

Several streams of literature – spanning innovation systems, triple helix, innovation clusters, and localised knowledge spillovers – have investigated the influence of proximity between university and industry on a variety of possible outcomes including: the probability to initiate UICs, their frequency, the quality of research output (a summary of key papers on the effects of proximity of various outcomes is presented in Table A1 in the Appendix). Most of these studies have focused on three types of proximity: geographical, institutional and cognitive. Geographical proximity indicates the closeness of the partners' locations. Institutional proximity refers to the closeness of the partners' institutional frameworks: it implies alignment of organisational practices, norms, routines and objectives (Amabile et al., 2001; Rynes et al., 2001). Cognitive (or knowledge) proximity denotes the presence of similar, complementary and aligned knowledge bases between partners (Brown and Duguid, 1998; Nooteboom, 2000). Yet, the literature has not discussed how proximity relates to the impact of UICs. These effects are likely to change depending on the types of impacts considered.

Table 1
Economic, knowledge, and social impact of UICs.

Type of impact	Knowledge	Economic	Social
Definition	Enrichment of the knowledge base of actors	Improvement in the economic condition of actors	Improvement in the functioning and performance of social organisations
Examples of impact	• Ideas for new scientific projects, new publications • New fundamental and applied knowledge, testing application of theories • New perspectives for the solution of problems • New innovation and R&D strategies • Improved use of knowledge for operations and strategic decision making • Improvement in curricula and teaching materials	• Improved revenue from new products, new processes and new markets, • Cost savings from new processes and lower internal R&D costs • New business opportunities, including new ventures • More industry funds for academic laboratories and research • More collaborations leading to more funding, including more government funding for research • More income from the commercialisation of research outputs	• Enhancement of cultural and social capital • Community formation • Improvements in the lives of certain social groups • Addressing social challenges • Shaping better policies

2.2. Proximity and impact: a conceptual model

A review of the literature discussing the types of impact generated by UICs suggests that most impacts can be subsumed under three main categories (Ankrah and Al-Tabbaa, 2015), which we term knowledge, economic, and social.[1] Table 1 illustrates different impacts of UICs that could be classified under each of these three broad types. Knowledge impact implies the enrichment of the knowledge base of the collaborators; economic impact offers improvements in their economic condition; while social impact consists of improvements in the functioning and performance of social organisations, beyond the collaborators themselves.

To understand the relationship between proximity and impact, we develop a conceptual model of the ways in which the knowledge produced by UICs can be used to generate different types of impact, by

[1] This categorisation is similar that proposed by Ankrah and Al-Tabbaa (2015) who distinguished between institutional, economic and social benefits, with their 'institutional' benefits category strongly overlapping with our 'knowledge' impact category. We prefer to use the term 'knowledge' impact to avoid confusion with the use of the term 'institutional' in relation to proximity.

adapting Bozeman's (2000) knowledge transfer framework.[2] Adapting Bozeman's terminology, we can describe the process of impact generation in terms of: the main *agents* that drive the interactions that generate impact; the main stakeholders who benefit from the UIC (impact *recipients*); the type of knowledge, collaboratively developed within the UIC, which enables impact to occur (impact *object*); the types of interactions through which impact occurs (impact *medium*).[3]

In the next three subsections, we describe the generation of each type of impact using Bozeman's conceptual categories, and we build on the literature on proximity and the economics of knowledge (Asheim and Gertler, 2005; Asheim and Coenen, 2005; Davids and Frenken, 2018) to develop hypotheses concerning the associations between proximities and types of impact.

2.2.1. Proximity and knowledge impact

UICs generate knowledge impact when they result in new knowledge that is of value to the collaborators, who are, therefore, the primary recipients of knowledge impact (Lee and Bozeman, 2005; Wuchty et al., 2007).[4] Knowledge impact is generated when the UIC produces new knowledge that could improve the knowledge bases of university and business partners. Interactions focused on the exchange of knowledge between collaborators are, therefore, the impact medium. The impact object is the knowledge that is produced and integrated to generate further knowledge, in the form of ideas for new scientific projects, new publications, improvement in curricula and teaching materials, improved knowledge for operations and strategic decision making.

The knowledge used for these purposes is usually analytical. Analytical knowledge helps to understand and explain empirical phenomena (Aslesen and Isaksen, 2010; Pinto et al., 2013); it is highly codified; it can be disembodied from the context in which it was generated and used in other contexts; and it generally plays a major role during the initial stages of the innovation process (Moodysson et al., 2008). The university is the main agent that has the resources and the motivation to develop analytical knowledge (Marques et al., 2006; De Silva, 2016). Therefore, the knowledge-based interactions that lead to the exchange of analytical knowledge are often driven by the university partner, even in the context of UICs that respond to a business need.

The integration of the analytical knowledge generated during the UIC with the collaborators' own knowledge base to produce knowledge impacts, is likely to be facilitated by the collaborators' cognitive proximity. In all kinds of collaborations, the presence of similar and complementary bodies of knowledge between the collaborators increases absorptive capacity (Hung et al., 2021) and shared understanding, making it easier to process, exchange and exploit knowledge (Nooteboom, 2000), so that partners can better integrate each other's knowledge to generate knowledge impacts. Cognitive proximity is also, or even particularly, important in order to generate knowledge impact in UICs. On the one hand, knowledge impacts on universities – such as new scientific projects, new publications, and improvement in curricula and teaching materials – are more likely to be produced in collaboration with businesses that have closer knowledge bases (De Silva et al., 2023), because businesses with cognitive proximity are more likely to be able to offer insights on practical applications and commercial insights (Marrocu et al., 2013) which enrich the more abstract knowledge base of the university. On the other hand, knowledge impacts on businesses – such as the development of improved knowledge for business operations and strategic decision-making – are more likely to occur when businesses collaborate with universities that have closer knowledge bases. In fact, cognitive proximity makes it easier to tailor the more abstract knowledge of the university to the practical needs of businesses, producing new knowledge that is of value to the latter (Hewitt-Dundas, 2013; De Silva et al., 2023). These arguments lead us to develop the following hypothesis:

H1a. Cognitive proximity has a positive association with the generation of knowledge impact.

As the university drives the interactions leading to knowledge impacts, business partners who are familiar with the organisational practices, social norms, routines and objectives of academics, will be better able to participate in knowledge production and sharing (Amabile et al., 2001; Rynes et al., 2001). Therefore, when interacting with those who are institutionally close to them (Alpaydın and Dahl Fitjar, 2021), universities and businesses can develop useful knowledge, which results in enhancing each other's knowledge bases (i.e. knowledge impacts). Universities' knowledge production being curiosity-driven and having a relatively greater long-term focus, could mean that their institutional frameworks are different from that of businesses, which have more target-oriented, short-term knowledge production processes (Compagnucci and Spigarelli, 2020). Therefore, especially in relation to generating knowledge impact, institutional proximity could result in the alignment of different knowledge production systems, and thus, it could facilitate interactive learning and joint knowledge production (De Silva and Rossi, 2018; Taheri and van Geenhuizen, 2016). The knowledge produced through such joint approaches, facilitated by institutional proximity, is more likely to result in academic publications and teaching materials as well as influencing business decision-making and operations (Thomas and Ambrosini, 2021). These arguments lead us to hypothesise:

H1b. Institutional proximity has a positive association with the generation of knowledge impact.

The type of knowledge used to generate knowledge impacts is analytical and codified (Aslesen and Isaksen, 2010; Pinto et al., 2013). It can be argued that geographical proximity is not so important for the exchange of analytical, codified knowledge that is general and not very contextualised, and can be quite easily transmitted over geographical distances (Herstad et al., 2014; Davids and Frenken, 2018). Due to these properties of analytical knowledge, universities and businesses that are not located in close proximity, can still collaborate to generate knowledge impacts in the form of improving their knowledge bases and associated decision-making (Ponds et al., 2010). It has also been argued that in the context of knowledge impact generation, often associated with analytical and codified knowledge, geographical proximity may in fact hamper the production of new knowledge (Sun and Cao, 2015). This leads to the following hypothesis:

H1c. Geographical proximity does not have a positive association with the generation of knowledge impact.

2.2.2. Proximity and economic impact

UICs achieve economic impact when the collaboration generates financial outcomes such as income or funding. While sometimes economic benefits spill over beyond the UIC, the main recipients of economic impact are usually the collaborators themselves.

Economic impact in the context of UICs is typically generated when academic knowledge is applied to the solution of a business problem. In such instances, the outcome of UICs leads to improved revenue from new products, new processes and new markets, cost savings, new

[2] While the process of knowledge generation within UICs is more complex than just knowledge transfer – many UICs involve the co-creation of knowledge between partners (De Silva et al., 2018) – the elements identified by Bozeman are useful when it comes to describing how UICs generate impact. In fact, impact occurs when the knowledge produced by UICs is used to benefit stakeholders, whether the collaborators themselves or others.

[3] The other dimension identified by Bozeman (2000), the demand environment, is less relevant since we are focusing on how impact is produced rather on how that impact is welcomed by those who can potentially receive it.

[4] Even though this new knowledge can subsequently feed into other activities benefiting those outside the collaboration (De Silva, 2016), this is not generally the primary objective of the production of new knowledge.

business opportunities, more research funds, and more income from commercialisation. The impact medium is, therefore, problem-solving interactions.

The type of knowledge that is used to solve business problems leading to economic impact (impact object) is often synthetic. Synthetic knowledge refers to know-how, is used to design solutions to practical problems, and is particularly tacit in nature (Asheim and Gertler, 2005; Asheim and Coenen, 2005; Davids and Frenken, 2018). The main agent that drives the interactions leading to the production and transmission of synthetic knowledge is usually the business partner. Even though the university's knowledge contribution is crucial to solving the problem identified by the business, it is the latter that sets the parameters for the definition of the problem and the criteria to decide whether the solution is satisfactory.

Finding solutions for business problems requires academics to work on-site and to interact with key business representatives to better understand the problem and to draw on the business' tacit knowledge (Davids and Frenken, 2018). Geographical proximity can facilitate frequent, face-to-face, close interactions, informal exchange of knowledge, and knowledge spillovers (Boschma, 2005; Salter and Martin, 2001; Iacobucci and Perugini, 2023) while reducing the cost of knowledge sharing (Storper and Venables, 2004). Thanks to such frequent, in-person interactions facilitated through geographical proximity (D'Este and Iammarino, 2010) universities and businesses are better able to integrate their tacit knowledge for commercialisation in order to generate economic impacts. Additionally, being in the same locality enhances mutual understanding of, and interactions with, the local business environment, associated supply chains, entrepreneurial ecosystem and business opportunities (Van Looy et al., 2003), which are crucial when using academic knowledge to offer business solutions during the UIC. It has also been identified in the literature that there are more grant funding opportunities to address business challenges for universities collaborating with local businesses, further supporting the positive effect of geographical proximity in generating economic impacts (Hong and Su, 2013). Therefore, we hypothesise that:

H2a. Geographical proximity has a positive association with the generation of economic impact.

Institutional proximity improves the collaborators' understanding of each other's institutional requirements, systems and processes (Bruneel et al., 2010; Muscio and Pozzali, 2013) and provides a platform to structure the relationship (Yli-Renko et al., 2001). In particular, since the generation of economic impact is mainly driven by the needs of business, it is important for the success of the problem-solving activity that the academic partner is familiar with business practices and routines. Academics who are familiar with business practices can integrate academic knowledge with business knowledge to resolve business challenges that during the UIC result in increasing income, reducing costs, and enhancing further business opportunities (Rosli et al., 2018). Also, institutional familiarity increases the chances of universities and businesses jointly securing grant applications (Hong and Su, 2013) – another form of economic impact – since they are better able to illustrate efficient collaboration to resolve business challenges. Therefore, we hypothesise that:

H2b. Institutional proximity has a positive association with the generation of economic impact.

Cognitive proximity, on the contrary, is likely to matter less, since solving business problems in novel ways, leading to economic benefits, requires the integration of diverse knowledge bases (Ernst and Bamford, 2005; Vlaisavljevic et al., 2016). Cognitive distance offers UICs the ability to pool diverse sources of knowledge (Nooteboom et al., 2007) leading to innovating economic solutions, which businesses expect to achieve through their collaborations with universities (De Silva and Rossi, 2018). Cognitive distance thus supports the integration of a novel combination of complementary resources and knowledge bases (Nooteboom et al., 2007), critical to generating economic impacts. Especially since businesses are better capable of generating economic impacts than universities (De Silva et al., 2023) unless the cognitive base of academics is different from that of businesses, novel economic solutions are unlikely to be generated and businesses rather generate economic impacts by themselves. It has also been highlighted that cognitive proximity is significantly less relevant for achieving direct economic impacts from technologies, compared to achieving social impacts (Janssen and Abbasiharofteh, 2022). We thus hypothesise:

H2c. Cognitive proximity has a negative association with the generation of economic impact.

2.2.3. Proximity and social impact

UICs that achieve social impact can engender durable improvements in the functioning of organisations and social groups (Reale et al., 2017). Therefore, stakeholders outside the collaboration are the main recipients of the social impact of UICs (Rossi et al., 2017; Crossick, 2009; Molas-Gallart et al., 2000). Social impacts can be varied: enhancement of cultural and social capital, community formation, improvements in the lives of social groups, and shaping better policies, among others. The knowledge underpinning the generation of social impact (impact object) can be of various kinds. For instance, if social impact is achieved through a specific intervention using technology, it might entail the production of synthetic knowledge. If social impact is achieved through the design of better policies, it might entail the production of analytical knowledge. In some cases, impact involves changing perceptions or culture that are shaped by symbolic knowledge (Davids and Frenken, 2018). What the interactions that lead to social impact have in common is the intention of the collaborators to aim for social outcomes. Hence, both universities and businesses (the agents) are likely to be co-driving social-diffusion oriented interactions (medium) with external stakeholders (Rosli et al., 2018; De Silva et al., 2019).

We expect geographical proximity to have a positive association with social impact. When the partners are co-located, they have a better understanding and care of local social challenges, and therefore they might be keener to generate benefits to the local area both directly and through spillover effects (D'Este and Iammarino, 2010; Hewitt-Dundas, 2013). Universities working with a local business partner might be particularly keen to showcase the impact on the locality (De Silva and Wright, 2019). As the generation of social impact may require universities and businesses to work closely with the beneficiaries (Cunliffe and Scaratti, 2017; Rossi et al., 2017; De Silva et al., 2019), it may be facilitated by both university and business partners being in geographical proximity to beneficiaries, and to each other. It has been highlighted that offering solutions to social problems requires close and frequent interactions with communities, that have a better understanding of the problems and community needs (De Silva and Wright, 2019). Therefore, frequent, face-to-face, close interactions, and informal exchange of knowledge facilitated through geographical proximity (Boschma, 2005; Salter and Martin, 2001; Iacobucci and Perugini, 2023) enable universities and businesses to generate social impacts. Therefore, we hypothesise that:

H3a. Geographical proximity has a positive association with the generation of social impact.

We also expect cognitive proximity to be important due to the need for both parties to focus on generating benefits for stakeholders outside the UIC, which is more likely when they are working in a similar sector and field of knowledge, because they are likely to be engaging with similar stakeholder communities (Rossi et al., 2017; Crossick, 2009; Molas-Gallart et al., 2000). Since neither universities nor businesses are direct beneficiaries, their understanding of the needs of society and how to use their respective knowledge bases to address social needs are enhanced when they come from the same discipline (Villani et al., 2017). Additionally, since generating societal impacts does not

Table 2
The generation of different types of impacts and associations with proximities.

Type of impact	Knowledge: enrichment of the knowledge base of actors	Economic: improvement in the economic condition of actors	Social: improvement in the functioning and performance of social organisations
Main impact recipients	UIC partners	UIC partners	Stakeholders outside the UIC
Impact medium	Knowledge-based interactions	Problem-solving interactions	Social diffusion-oriented interactions
Main impact agent	University	Business	Both university and business
Impact object	Analytical knowledge	Synthetic knowledge	Various: analytical, synthetic or symbolic
Geographical proximity	Expected lack of association	Expected positive association	Expected positive association
Institutional proximity	Expected positive association	Expected positive association	Expected lack of association
Cognitive proximity	Expected positive association	Expected negative association	Expected positive association

constitute core activities of universities and businesses but rather they are driven by universities' and businesses' social orientations (Rocancio Marin, 2022), cognitive proximity would enhance their ability to integrate their knowledge bases to generate social impacts, with which they are less familiar. This leads us to hypothesise that:

H3b. Cognitive proximity has a positive association with the generation of social impact.

Instead, we expect institutional proximity between universities and businesses to be less important for the generation of social impact. This is mainly because, since the beneficiaries of social impacts are stakeholders outside the UIC, universities and businesses are more likely to interact with societal institutional structures (Cowan et al., 2000) rather than between the institutional structures of universities and businesses. Since social value creation is not a core activity of universities (Qiu et al., 2023) or businesses (Dupire and M'Zali, 2018), having an understanding each other's norms, systems and procedures, which are predominantly designed to facilitate core activities (Bruneel et al., 2010; Muscio and Pozzali, 2013) is less likely to facilitate the generation of social impacts. This leads to the following hypothesis:

H3c. Institutional proximity does not have a positive association with the generation of social impact.

Table 2 summarises our conceptual model and hypothesised associations between proximities and impacts.

Different types of proximities can interact with each other in non-linear ways. For example, Ponds et al. (2007) and Crescenzi et al. (2017) find that geographical and institutional proximity act as substitutes in facilitating the initiation of UICs, and Lander (2015) finds the same in the context of research networks. Instead, Marek et al. (2017) find that while different types of proximity influence the emergence of R&D collaborations, there are no substitution effects; while Johnston and Huggins (2017) and Gomes Santos et al. (2021) find positive synergies between geographical and cognitive proximity in promoting UICs. Santamaria et al. (2021) find that geographical proximity combined with cultural proximity facilitates the successful development of innovations from technological collaborations. These studies consider different objects of analysis (R&D collaborations funded by the government, co-authorship networks, co-patents) and different combinations of proximities, they report conflicting results, and they mainly focus on the probability to initiate collaborations, not on the impact of these collaborations. Due to the lack of prior theorisations of the relationship between interactions between proximities and impact, it is not possible to develop expectations on the influence that interactions between proximities might have on the generation of different types of impact. Hence, we test for the presence of interaction effects in our empirical analysis without developing formal hypotheses concerning those effects.

3. Data and methodology

3.1. Data: Knowledge Transfer Partnership (KTP) scheme

The Knowledge Transfer Partnership (KTP) scheme, launched in 2003 by the UK government, enables organisations to take advantage of expertise within universities. Each KTP is a partnership between an 'academic partner' (which can be a university department, a public research laboratory or another research organisation) and a 'business partner' (which – despite the use of the 'business' term – can be any public, private for-profit, or private non-profit organisation). The scheme involves the recruitment of a recently qualified graduate ('associate') working under joint supervision from the business and academic partners, tasked with completing a project that addresses a need of the business partner. Each partnership lasts between 12 and 36 months, and it is part-funded with public funding (up to 66 %, depending on the organisation size), with the balance of the funds coming from the business partner. The KTP scheme aims to facilitate knowledge exchange and business innovation (Ternouth et al., 2012; Wynn and Turner, 2013). Even though its name refers to 'knowledge transfer', in practice its purpose is to facilitate close interactions between the partners leading to the co-creation of knowledge between different organisations (Ternouth et al., 2012). The collaborators are free to select their partners, to decide how the UIC is organised and managed, to continue their collaboration after the end of the KTP, and to seek additional funding (Rosli et al., 2018).

Each completed KTP is required to produce a final report describing its impact, including several quantitative indicators (such as improvements in turnover, exports, profit before tax, investment) that can be directly attributed to the KTP. The final report is graded by an independent review panel. While the final reports and evaluations are confidential, the funding agency released shorter reports relating to 423 KTPs completed between 1999 and 2012. These reports followed a consistent structure detailing the impacts of the KTP. They provide the evidence base for our analysis: 415 usable documents, after eliminating duplicates and case reports in languages other than English (two were in Welsh). As discussed in the next section, these reports and secondary data on KTPs were combined as the main sources of data for the analysis.

To increase internal validity of the impact measure and the quantitative findings we also carried out in-depth interviews with seven individuals who were involved in eleven of the 415 KTPs (two individuals participated in three different KTPs each). These seven interviews were performed between 2014 and 2015 as part of a larger qualitative project. Interviewees (Table 3) were purposefully chosen based on predefined criteria (purposive sampling) and recommendations by other interviewees (snowball sampling). In particular, these interviewees were associated with KTPs that were identified in our analysis of reports using topic detection – discussed in the next section – as having high knowledge, economic and/or social impacts. Academics and associates, directly involved in those KTPS, were selected as interviewees since they had a broader understanding of three different types of impacts, including those resulted from resolving business challenges. Additionally, due to the REF (Research Excellence Framework) exercise requiring evidence of impacts, academics had detailed recording of impacts, and thus, interviewing academics offered more reliable information on impacts generated through KTPs. Since interviews were used to validate our quantitative findings, this approach is considered appropriate (De Silva et al., 2018). The interviews were held for 60–90 min and transcribed. The interview questions are reported in the Appendix. The interview transcripts were independently coded using Nvivo by three researchers, seeking to identify key themes related to the research

Table 3
Details of interviewees.

ID	Title	Organisation	Role in KTP	N KTPs
1	Professor	University, Department of Engineering	Academic partner	1
2	Professor	University, School of Management	Academic partner	3
3	Professor	University, Department of Design, Manufacturing & Engineering Management	Academic partner	3
4	Centre Manager	University, School of Jewellery	Academic partner	1
5	Senior Lecturer	University, School of Applied Sciences	Academic partner	1
6	Product and Service Development Consultant	Environmental consultancy	Associate	1
7	Professor	University, Dept of Education & Professional Studies	Academic partner	1

question (Braun and Clarke, 2006; Saldaña, 2013). The outcomes of this initial coding were then discussed and agreed collectively by the research team.

3.2. Construction of measures of impact using topic detection

The success of UICs has been measured using participants' subjective evaluations (Stock and Tatikonda, 2000; Barnes et al., 2002; Mora-Valentin et al., 2004) or quantitative indicators capturing some of the outputs of the UIC, such as joint publications and joint patents (Becker and Dietz, 2004; Siegel and Leih, 2018). However, these indicators are not necessarily capturing the UIC's impact. For example, the participants' satisfaction with the collaboration is not necessarily correlated with its outcomes (Bekkers and Bodas Freitas, 2008), and the generation of outputs might not lead to impact if these are not implemented or disseminated. Some studies have attempted to capture impact by collecting information about longer-term outcomes generated by the UIC, such as: implementation or commercialisation of outputs (Fernald et al., 2015), development of long-term competences (Stock and Tatikonda, 2000), continuation of the collaboration (Bouty, 2000; Mora-Valentin et al., 2004), emergence of new linkages (Giuliani and Arza, 2009) and new business opportunities (Rosli et al., 2018). These exercises require ad hoc data collection efforts, which are costly, not easily comparable, and often refer to small samples (Bornmann, 2013).

We propose an original approach based on topic detection to capture the types of impact of UICs, by exploiting impact reports produced by the collaborators. These textual documents constitute extensive, fairly standardised and often easily collectable sources that can be mined for information. We develop quantitative measures of the extent to which different UICs' reports discuss impacts of different types; these are useful to differentiate the UICs in relation to the types of impact that they produce, under the assumption that UICs that use more intensively a dictionary of words relating to a certain type of impact are more oriented towards achieving that type of impact compared to UICs that use that dictionary less intensively.

To identify and measure the different types of impact generated by the 415 UICs as described in their short impact reports,[5] we proceeded in three steps: (i) lexical analysis aimed at identifying lexical units (content words and multiword expressions); (ii) identification of the impact themes present in the texts; (iii) ranking of the documents based on the impact themes identified. The methodology followed to identify the impact themes, corresponding to the steps (i) and (ii), is described in the Appendix. This entails identifying dictionaries of words capturing different dimensions of impact. In particular, we identified seven 'impact dictionaries', each of which captures a different impact dimension – some of these pertain primarily to the business (organisational information collection, organisational competences, financial and economic outcomes, production process / operations), some primarily to the university (teaching and research) and some to the broader socio-economic environment (society and environment, education) (see Table A3 in the Appendix).

Once we identified these seven 'impact dictionaries', we then proceeded to step (iii) which was to rank the documents based on the impact themes identified. We computed scores measuring the relevance of each report to each of the seven impact dictionaries we found, using the term frequency–inverse document frequency (TF-IDF) formula (Salton and Buckley, 1988; Salton, 1989). This formula assigns a score to each report according to how well that report fits a particular impact dictionary. The TF-IDF (see the Appendix for a more detailed description) is increasingly used in innovation studies (Woltmann and Alkaersig, 2017), although to our knowledge it has not yet been implemented to the specific analysis of impact. While attempts to improve the original TF-IDF formula have been proposed in recent years to adapt analyses to various texts and researchers' objectives, the choice depends on the characteristics of the textual documents under analysis. In our case, the objective is to measure the importance of a term in a document relative to its rarity in the entire document collection. Therefore, in the context of obtaining a ranking of documents based on lexical queries, TF-IDF stands as a robust choice, and by far the most widely used in the literature, delivering substantial results in identifying the most relevant documents for specific queries.

By computing the TF-IDF index of each document with respect to each of the seven impact dictionaries, we derived seven variables corresponding to each of the impact dimensions[6] (summary statistics are

Table 4
Impact dimensions variables: summary statistics.

Variable	Obs	Mean	Standard deviation	Minimum	Maximum
Organisational information	415	0.025	0.015	0.003	0.120
Organisational competences	415	0.020	0.014	0.000	0.106
Teaching and research	415	0.020	0.012	0.000	0.113
Financial and economic outcomes	415	0.019	0.015	0.000	0.123
Production process/ operations	415	0.030	0.025	0.001	0.150
Education	415	0.021	0.012	0.000	0.090
Society and environment	415	0.020	0.026	0.000	0.179

[5] The smaller document contains 398 words occurrences, while the largest contains 1218 words occurrences, with an average of 918 words occurrences per document (less than two standard text pages).

[6] For example, the document with the highest TF-IDF value for the Organisational information dictionary (TF-IDF equal to 0.120) contains 15 different words present in this dictionary, of which the most frequent are "data" and "statistical" with frequencies in the document of 1 % and 1.3 % respectively (9 and 13 occurrences out of 945), and these are much higher than the frequencies of "data" and "statistical" in the overall document collection, which are 0.09 % and 0.008 % respectively. The document with the lowest TF-IDF value for the Organisational information dictionary (TF-IDF equal to 0.0315) contains only four words present in the dictionary. As all documents in our collection contain at least one element of this dictionary, this explains why the TF-IDF of the Organisational information dictionary has a minimum value greater than zero (Table 4).

Table 5
Impact dimensions variables: principal components' loading factors after imposing a varimax rotation.

Impact type	Variable	Factor loading	Reliability
Knowledge impact on knowledge intensive activities of business and university	Organisational information	0.699	Eigen Value 1.141; Variance explained 38.025 %
	Organisational competences	0.698	CR- 0.636
	Teaching and research	0.407	
Economic impact on operational activities of business	Financial and economic outcomes	0.733	Eigen Value 1.075; Variance explained 53.773 %
	Production process / operations	0.733	CR- 0.699
Social impact on external stakeholders	Society and environment	0.727	Eigen Value 1.058; Variance explained 52.915 %
	Education	0.727	CR- 0.691

reported in Table 4).

We validated our seven impact measures in three ways. First, the measures were checked against the narrative impact descriptions presented in reports with selected TF-IDF values.[7] Second, for the KTPs whose participants were interviewed, we checked our measures of impact against the interview transcripts, to ensure that our impact measures were aligned to their account of the impact of the KTP.[8] Third, to further validate categorisation of theme labels to impact types presented in Table 4 and to facilitate the interpretation of patterns in our data by reducing the number of relevant impact dimensions, we ran a principal component analysis (PCA) on the seven impact variables. The analysis returns three highly significant components with eigenvalues >1, and satisfactory reliability measures (Table 5). Aligning the PCA findings with the validation steps discussed above further supported the use of this method to capture the type of impact generated by UICs. Additionally, the PCA allowed us to derive the dependent variables to be used in our empirical model: in fact, the first component (which is aligned with impact on organisational information collection, organisational competences and teaching and research activities) refers to knowledge impact, the second component (aligned with impact on production process and operations and with financial and economic outcomes) refers to economic impact, and the third component (aligned with impact on society and environment and education) refers to social impact. After the PCA, we derived factor scores for the three significant components, creating three variables that we named, respectively *Knowledge impact*, *Economic impact and Social impact*. These constitute the dependent variables in our empirical models.

3.3. Independent and control variables

Independent and control variables have been derived from information contained in the publicly available database of funded KTP projects.[9] This is a different source from the impact reports used to construct the dependent variables, and mitigates the danger of common method bias in the analysis. *Geographical proximity* takes value 3 if the company and the university are in the same postcode area, 2 if they are in the same region but different postcode areas, 1 if they are in different regions.[10] To measure *Institutional proximity*, we use the number of different KTP projects that the company and the university have engaged in prior to the current one, as a measure of their familiarity with each other's organisational practices, norms, routines and objectives (Paier and Scherngell, 2011; D'Este et al., 2013). Since the variable is skewed, and for consistency with the other independent variables, we transform it into an ordinal variable with thresholds corresponding to the first, second and third quantiles of the distribution. *Cognitive proximity* is an ordinal variable capturing the number of matches (at the one-digit level) between the company's SIC codes and the department's OECD FOS (Field of Science) codes, based on a concordance matrix between SIC codes and OECD FOS codes (Smolinski et al., 2015). This variable takes value 1 for no matches, 2 for 1 match, 3 for more than one match.

Table 6 lists our control variables, and presents the rationales for including them in the models. Table 7 reports key descriptive statistics on dependent, independent and control variables, while Table A4 in the Appendix reports the correlation matrix between dependent, independent and control variables.

3.4. Model

We ran multivariate regressions with knowledge impact, economic impact and social impact as dependent variables, three proximity dimensions as independent variables, and several controls. We use multivariate regressions because we expect our dependent variables (the different types of impact) to be generated together by a single process using the same predictor variables. While producing the same individual coefficients and standard errors as separate OLS regressions, the multivariate regression estimates the between-equation covariances, allowing to test coefficients across equations.

Since we are only observing UICs that have actually taken place, and we do not know what the partner selection criteria were, it is theoretically possible that in some cases, partner selection was influenced by the objective to achieve a specific type of impact, which would introduce an

[7] For each of the 7 impact variables, we identified the highest and lowest TF-IDF values and retrieved the reports corresponding to those values. One of the researchers (different from the person who had computed the indexes) then independently read the reports to confirm that the narrative contents of the reports reflected the impact dimension emerging from the TF-IDF.

[8] For example, for one of the KTPs which had a relatively high value of 'Production process / operations' impact, the interviewee stated that: *"The technology was coming in off the shelf but it was very new. The software and the technology were on a massively steep curve. They've now shouldered off but at that time and for about six years, they were going up like a rocket". [Interviewee 1].* Another example is in relation to a KTP which had a relatively high value of 'Organisational competences' impact, where the interviewee stated that: *"The regional development agency at the time was very interested in using it as a regional prime, so using that as the sort of company where it acted as a bridge between the international standards that would be required, and the local boat builders and so on, with a view to improving the quality of the local boat builders, raising them to international standards." [Interviewee 2]*

[9] The database is available from: http://ktp.innovateuk.org/search.aspx (last accessed January 2024).

[10] We consider the ordinal specification suitable to measure geographical proximity, since we expect proximity to relate non-linearly with impact, increasing according to thresholds which enable interactions on a very frequent (daily or weekly), frequent (twice monthly), or less frequent (less than monthly) basis. This is what our variable attempts to capture, in line with other studies that have analysed the effects of proximity on probability and quality of interactions (see for example Audretsch et al., 2006). Having an ordinal variable with different thresholds of commutable distance instead of an absolute distance variable also makes sense since the average distance between partners can be very different in different datasets (Johnston and Huggins, 2017) in fact using ordinal geographical distance measures is common in studies including subgroups with different mean distances (Heylen et al., 2014).

Table 6
List of control variables.

Variable name	Type	Description	Rationale for inclusion
Senior academic	Binary	Whether the academic mentioned as representative of the academic partner is a professor	A senior academic's reputation and connections might facilitate both knowledge impact – more publications, more extensive communication of project-related knowledge – and social impact. We do not know whether the academic mentioned as representing the academic partner in the KTP database is actually the person carrying out most of the work in the KTP: a senior academic might lend their name to the project while allowing more junior academics to do most of the actual engagement (Albert et al., 2012). Nonetheless the involvement, even if nominal, of the senior academic can lend more credibility to the project (Johnston and Huggins, 2018) and facilitate the academic connections which can potentially create knowledge and social impact.
Local funder	Continuous	Share of funding from regional funding bodies	Local funders might be particularly interested in social impact for their communities. Having more funders might require projects to demonstrate greater variety of impacts.
N funding bodies	Continuous	Number of different funders	
Grant amount	Continuous	Grant amount of the project	Better funded projects might have more resources to generate impact.
Organisational, process and product	Binary	Type of innovation the project focused on, manually coded from the project descriptions	Different types of innovation may be more likely to produce different types of impact
SME, Non profit	Binary	Whether the business partner is a small firm or a not for profit organisation	Different types of firms may be more likely to seek different types of impact
Firm_high_tech_manufacturing Firm_KIS Firm_other_manufacturing Firm_other_services	Binary	Sector of the company: high tech manufacturing, knowledge intensive service (KIS), other manufacturing and other services	Firms in different sectors may be more likely to seek different types of impact. For high tech manufacturing, we use the Eurostat definition, which includes the following NACE 2-digit sectors: (24) chemicals and pharmaceuticals; (29) machinery and engines; (30) computers and office machinery; (31) electrical machinery; (32) IT and communication equipment; transport equipment. For knowledge-intensive services, we use the Eurostat definition which includes the following NACE 2-digit sectors: (61) water transports; (62) air transports; (64) post and telecommunications; (65) financial intermediation; (66) insurance; (67) auxiliary activities to financial intermediation; (70) real estate; (71) renting of machinery and equipment; (72) computer related activities; (73) research and development; (74) other business activities; (80) education; (85) health and social work; (92) recreational, cultural and sporting activities.
Agriculture Medical Social Humanities Technology	Binary	Type of university department (agricultural sciences, medical and health sciences, social sciences, humanities, engineering, technology and natural sciences)	Academic partners specialised in different subject areas may be more likely to support different types of impact.

Table 7
Descriptive statistics on dependent, independent and control variables.

	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variables	Knowledge impact	415	0.00	1.11	−3.18	4.62
	Economic impact	415	0.00	1.09	−3.32	5.39
	Social impact	415	0.00	1.10	−4.82	5.05
Independent variables	Geographical proximity	415	2.02	0.75	1.00	3.00
	Institutional proximity	415	1.98	0.82	1.00	3.00
	Cognitive proximity	415	2.61	0.65	1.00	3.00
Control variables: policy	Local funder	415	0.14	0.27	0.00	1.00
	N funding bodies	415	1.29	0.47	1.00	3.00
	Grant amount	415	75,482	29,870	0.00	258,384
Control variables: partners	Senior academic	415	0.40	0.49	0.00	1.00
	SME	415	0.82	0.39	0.00	1.00
	Non profit	415	0.09	0.29	0.00	1.00
Control variables: type of innovation	Organisational	415	0.28	0.45	0.00	1.00
	Process	415	0.29	0.46	0.00	1.00
	Product	415	0.33	0.47	0.00	1.00
Control variables: business sector	Firm high tech manufacturing	415	0.23	0.42	0.00	1.00
	Firm KIS	415	0.33	0.47	0.00	1.00
	Firm other manufacturing	415	0.26	0.44	0.00	1.00
	Firm other services	415	0.13	0.34	0.00	1.00
Control variables: university department	Agriculture	415	0.01	0.98	0.00	1.00
	Medical	415	0.05	0.22	0.00	1.00
	Social	415	0.31	0.46	0.00	1.00
	Humanities	415	0.05	0.21	0.00	1.00
	Technology	415	0.58	0.49	0.00	1.00

Table 8
Multivariate regressions.

	Model 1			Model 2		
	(a)	(b)	I	(I(e)	(f)	
VARIABLES	Knowledge impact	Economic impact	Social impact	Knowledge impact	Economic impact	Social impact
Geographical proximity	*0.114*	0.187***	−0.179***	0.114	0.336	−0.176
	(0.078)	(0.072)	(0.069)	(0.342)	(0.315)	(0.300)
Institutional proximity	0.042	0.026	−0.203***	0.666*	0.687**	−0.272
	(0.068)	(0.063)	(0.060)	(0.347)	(0.320)	(0.304)
Cognitive proximity	0.097	−0.025	−0.020	0.422	0.156	*−0.459*
	(0.095)	(0.088)	(0.083)	(0.318)	(0.293)	(0.279)
Cognitive*geographic				0.042	0.054	0.091
				(0.114)	(0.105)	(0.100)
Institutional*geographic				−0.052	−0.143*	*−0.123*
				(0.091)	(0.084)	(0.080)
Cognitive*institutional				−0.200*	*−0.143*	0.123
				(0.103)	(0.095)	(0.091)
Senior_academic	0.149	−0.216**	0.093	0.157	−0.209**	0.087
	(0.114)	(0.105)	(0.100)	(0.114)	(0.105)	(0.100)
Local_funder	*−0.330*	0.532***	0.865***	−0.310	0.557***	0.863***
	(0.219)	(0.202)	(0.193)	(0.220)	(0.202)	(0.193)
N_funding_bodies	0.083	0.058	0.320***	0.064	0.057	0.350***
	(0.127)	(0.117)	(0.111)	(0.128)	(0.118)	(0.112)
Grant_amount	0.000	0.000	−0.000*	0.000	0.000	*−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SME	0.414***	0.331**	−0.064	0.412***	0.311**	−0.096
	(0.152)	(0.140)	(0.134)	(0.153)	(0.141)	(0.134)
Non_profit	−0.175	−0.243	0.311*	−0.179	−0.247	0.317*
	(0.211)	(0.195)	(0.185)	(0.211)	(0.194)	(0.185)
Organisational	−0.027	−0.009	0.252	−0.020	−0.020	0.218
	(0.225)	(0.208)	(0.198)	(0.226)	(0.208)	(0.198)
Process	−0.060	0.055	−0.019	−0.066	0.040	−0.030
	(0.223)	(0.206)	(0.196)	(0.223)	(0.205)	(0.195)
Product	−0.218	−0.222	−0.181	−0.229	−0.250	−0.205
	(0.220)	(0.203)	(0.193)	(0.221)	(0.203)	(0.193)
Firm high tech manufacturing	0.212	0.061	−0.485*	0.242	0.090	−0.491*
	(0.288)	(0.265)	(0.253)	(0.288)	(0.265)	(0.252)
Firm KIS	0.326	−0.550**	−0.243	0.308	−0.572**	−0.249
	(0.288)	(0.265)	(0.253)	(0.288)	(0.265)	(0.252)
Firm other manufacturing	0.204	−0.072	−0.167	0.188	−0.094	−0.167
	(0.289)	(0.266)	(0.254)	(0.289)	(0.266)	(0.253)
Firm other services	0.292	−0.155	−0.202	0.300	−0.162	−0.215
	(0.311)	(0.287)	(0.273)	(0.312)	(0.287)	(0.273)
Agriculture	0.088	0.116	0.206	0.138	0.246	0.308
	(0.563)	(0.520)	(0.495)	(0.569)	(0.524)	(0.499)
Technology	−0.206	0.091	−0.274**	*−0.219*	0.077	−0.282**
	(0.145)	(0.134)	(0.127)	(0.145)	(0.134)	(0.127)
Humanities	−0.637**	0.867***	−0.256	−0.592**	0.903***	−0.277
	(0.280)	(0.259)	(0.246)	(0.281)	(0.259)	(0.246)
Medical	−0.451*	0.022	0.857***	−0.478*	−0.019	0.829***
	(0.264)	(0.244)	(0.232)	(0.265)	(0.244)	(0.233)
Constant	−1.025**	−0.545	0.873**	−2.019**	−1.527*	1.534*
	(0.493)	(0.455)	(0.433)	(0.992)	(0.914)	(0.870)
Observations	415	415	415	415	415	415
R-squared	0.082	0.184	0.274	0.091	0.194	0.284
F	1.763	4.439	7.442	1.170	4.071	6.719
P-value	0.023	0.000	0.000	0.023	0.000	0.000

Note to Table 8: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Italics*: $p < 0.15$.

Table 9
Summary of findings.

	Sign of association between proximity and type of impact		
Type of proximity:	Knowledge impact	Economic impact	Social impact
• Geographical	No effect	+	−
• Institutional	+	+	−
• Cognitive	No effect	No effect	No effect
• Cognitive*Institutional	−	No effect	No effect
• Institutional*Geographical	No effect	−	−
• Cognitive*Geographical	No effect	No effect	No effect

− - Significantly negative effect; + - Significantly positive effect

element of endogeneity in the model. Still, there are a number of reasons why endogeneity is unlikely to be a serious problem with this data. First, the impact reports were written a number of years after the KTP ended, which suggests that the impact they captured were not all likely to have been foreseen at the time in which the partner selection occurred. Secondly, the short impact reports, while based on the KTP's final reports as well as other information, were written by the funding agency rather than by the collaborators themselves, which further increased the distance between the impact described and the intentions of the collaborators at the start of the UIC. Third, we have included numerous control variables to capture unobserved processes influencing both the choice of partners (in relation to their proximity) and potential impact. Fourth, as a robustness check, we have included a version of the model with instrumental variables, which should remove the problem of endogeneity. Still, due to the residual presence of potential endogeneity issues, we refrain from using causal language when discussing our empirical results but we only talk of associations between variables capturing proximity and impact.

4. Analysis

4.1. Empirical model

We ran multivariate regressions with knowledge impact, economic impact and social impact as dependent variables, three proximity as independent variables, and several controls. Table 8 shows two multivariate regressions. Model 1 includes the three proximity variables as dependent variables, while Model 2 adds three interaction terms between the independent variables: cognitive*geographic, institutional*geographic, and cognitive*institutional.[11]

Considering knowledge impact - columns (a), (d) – in both models we find positive, although not significant, associations with cognitive proximity; despite the coefficients being aligned with the expectations for H1a, this hypothesis is not supported. We also find a positive but not significant association of knowledge impact with institutional proximity (column a); the positive association between knowledge impact and institutional proximity becomes significant only when interaction terms are included, and the interaction between institutional and cognitive proximity is negative and significant (Model 2, column d). Hence, while institutional proximity itself has a positive association with knowledge impact (thus supporting H1b), when institutional proximity is combined with cognitive proximity this has a negative association with knowledge impact. In other word, the collaborators' norms and routines need to be close so that they can effectively share knowledge; however, excessive closeness of the collaborators' norms and routines and of their knowledge bases might constrain the novelty of the knowledge produced. We can argue that there is a substitution effect between cognitive and institutional proximity. We also find that geographical proximity has a non-significant association with knowledge impact, both individually and in interaction with other proximity variables, thus supporting H1c.

Considering economic impact – columns (b), I – we find a positive and significant association with geographical proximity in Model 1 (column b), supporting H2a. Institutional proximity is positively but not significantly associated with economic impact (column b). However, when we introduce interaction terms (Model 2, column e), we find that the institutional proximity coefficient is positive and significant, supporting H2b. In this model, we note that the interaction of institutional and geographical proximity is negatively associated with economic impact. Hence, while institutional proximity itself has a positive association with economic impact, when institutional proximity is combined with geographical proximity this has a negative association. Having both geographical and institutional proximities might result in excessive familiarity between the partners. This might lead them to rely heavily on their existing network (Oliver, 2004) which might reduce the UIC's capability to solve pressing and novel business problems and hence their economic impact.

We also find that cognitive proximity has a negative (though non-significant) association with economic impact, both individually and in interaction with other proximity variables, thus partially supporting H2c.

Finally, considering social impact – columns (c), (f) – contrary to expectations we find that both geographical proximity and institutional proximity have negative associations with social impact. Hence, the data do not support hypotheses H3a and H3c: geographical and institutional *distance* between the collaborators are important for social impact. It is possible that social impacts are linked to the achievement of complex social challenges, and that these are best addressed when local firms work together with distant universities, usually more research-intensive than local ones. When we include the interaction terms, both proximities lose significance, while the interaction term is negative, but also marginally non-significant. Perhaps UICs with partners that are both located closely and have experience of working with each other tend to work on more immediate business challenges which are less likely to

[11] In all models, the three equations that compose each multivariate regression are significant, individually as well as together, as it is shown by the Manova tests reported in Table A5 in the Appendix. The Breusch-Pagan test of independence does not reject the null hypothesis of independence between the residuals of the three equations (chi2(3) = 0.491, Prob>chi2 = 0.921).

have social impacts outside the UIC.

We also find that cognitive proximity has a non-significant association with social impact, both individually and in interaction with other proximity variables, thus not supporting H3b.

Table 9 summarises the effects of the independent variables and their interactions on the three types of impact.

The effects of the controls are robust across all models. The involvement of a senior academic is positively but not significantly associated with knowledge impact, and it is negatively associated with economic impact. Perhaps senior academics are less invested in contributing to projects whose outputs are mainly geared towards the business. The share of funds from local funders is positively associated with both social and economic impact: local funders might require projects to benefit the local community, and they might be particularly interested in projects that demonstrate economic outcomes, inducing KTP partners to particularly seek to deliver these impacts and to emphasise them in their final reports. Instead, the share of funds from local funders is negatively associated with knowledge impact: local funders are probably less interested in the production of knowledge outputs, which are less closely related to the promotion of local development, so these impacts are less sought after by KTP participants, and less emphasised in the reports.

The number of funders has a positive association with social impact, perhaps because the projects must be shown to benefit a broader range of stakeholders in order to satisfy a broader variety of funders. Greater grant amount has a negative association with social impact, perhaps because funders tend to provide fewer resources to projects that have social objectives. The involvement of SMEs is associated with greater economic and knowledge impact. A detailed inspection of the dataset shows that many of the large organisations are from the public sector (National Health Service Trusts, public research bodies), where collaborations place more emphasis on social impact and less on other impacts.

Industry effects are significant for economic and social impact. UICs that involve KIS firms emphasise economic impact less; perhaps these companies participate in KTPs in order to improve their knowledge resources rather than to produce operational results. UICs that involve high tech firms tend to emphasise social impact less, while UICs that involve not-for-profit organisations tend to emphasise social impact more: while not-for-profit organisations need to respond to criteria of financial sustainability (de Silva and Wright, 2019), their typical objectives are linked to achieving socially relevant outcomes. There are significant effects for certain university departments in relation to all impact types.

4.2. Robustness checks and validation

In order to substantiate our findings, we proceeded in two ways. First, we employed several robustness checks whereby we ran the models again using different specifications. Second, we used qualitative evidence from the interviews to validate our findings, by identifying statements which emphasised the importance of relevant proximity dimensions in the context of KTPs that generated specific types of impact.

The robustness checks involved implementing several simple variations of the full Model 2: running separate OLS regressions on the three variables *Knowledge impact*, *Economic impact*, *Social impact*; transforming the three dependent variables into binary (using the mean as the threshold); running separate logit regressions; In all cases the signs and significance levels of coefficients are maintained.[12] We also ran a more complex version of the full model (Model 2) using a two-stage least square model with instrumental variables, in order to attempt to address potential endogeneity issues arising from reverse causality (in case the choice of collaborators with specific types of proximity was driven by the intention to obtain a certain impact) and/or from omitted variables. In in the instrumental variables model (shown in Table A6 in the Appendix) all the signs of the coefficients are maintained, and in most cases also their significance.

In order to validate our findings, we also identified quotations that supported the relationships that appeared to be significant from our empirical models. Institutional proximity was found to have a positive association with knowledge impact and economic impact, and a negative association with social impact. In relation to knowledge impact, an interviewee remarked on the need for an academic who understands business norms in projects that impact the competences of the business: "*the academic supervisor or the lead academic is getting very relevant, up-to-date industry experience which they can then transfer to their [KTP associate] that help successful project outcomes*". [Interviewee 4].

In relation to economic impact, an academic involved in a KTP that generated significant economic outcomes remarked on the importance of institutional proximity: "*I talked to them, we talked about the Engineering bit, that is why we got on, because I could understand what they were talking about, that they talked to other people, but the people I talked to in their language, I talked to them in their language, we got the project going*" [Interviewee 5].

In relation to social impact, we found that a project with an innovative outcome with high social impact was characterised by institutional distance: "*I think it's very fascinating to work with [institutional] resistance and try and build bridges you know and work in an interdisciplinary way and you know, it is innovation […] – it's interesting and worthwhile to try and shift people so yeah, I think that's all been worthwhile*" [Interviewee 7].

Geographical proximity was found to have a positive effect on economic impact and a negative effect on social impact. In relation to economic impact, an academic remarked on the importance of geographical proximity for identifying business problems whose solution generates economic impact "*One of the things that happened, just because I was there physically in the building and drinking coffee with them, that I started talking with them and saying this looks a big problem, they have got this problem, what we want to do*" [Interviewee 5]. In relation to social impact, it was evident that local universities might not be the ideal partners. In fact, geographical distance, that would bring new initiatives/ideas from other places, may offer the required change: *"We've just got one at the new campus in Qatar and the foyer and the opening site is one of our digital exhibits so there's […] various different apps designed to engage and excite people."* [Interviewee 1].

We found a negative effect of the interaction between cognitive and institutional proximity in relation to knowledge impact. The interviews confirmed that a project with high cognitive and institutional proximity (the company was in the same sector as that of the academic, and the academic had previous relevant industry experience) did not produce new knowledge because the company believed they did not have anything to learn from academics with close knowledge and experience "*It was just never gonna work, and they basically weren't interested in the jewellery experience that myself and my colleague, who was the academic supervisor, had. My colleague, who's our technical manager, used to be a production manager in a jewellery company. They weren't interested in that.*" [Interviewee 3].

We also found a negative effect of the interaction between geographical and institutional proximity, in relation to both economic and social impact. One interviewee discussed how they sought to work with a sector they are experienced with, when they cannot have geographical proximity, thus, treating these forms of proximity as substitutes: "*Specific large companies where I've learnt the sector. For example, Aerospace I'm…I hope I'm reasonably good at. Automotive I've not touched. One of the things about being in London is you're away from that core specific company, so the West Country, Midlands, so the logistics of getting in and out of these things mean that …well I tend to focus [on the sector I know]*" [Interviewee 1].

[12] The results of these robustness checks are available from the authors upon request.

5. Discussion

5.1. Theoretical contribution

The paper addresses an important gap in our knowledge of the association between proximity and impacts of UICs (Steinmo and Lauvås, 2022). Understanding the different facets of proximities and their association with different types of impacts generated by UICs is important to strategically form successful collaborations based on expected impacts, due to vast differences between universities and businesses (Bertello et al., 2022). Theoretically, we have built a conceptual model combining Bozeman (2000)'s model of knowledge transfer with the literature on the economic properties of knowledge (Asheim and Gertler, 2005; Asheim and Coenen, 2005) and developed hypotheses linking different types of proximity to different types of impact. Our findings make an original contribution demonstrating how different types of impact are associated with different facets of proximities between universities and businesses in different ways.

First, we demonstrate that geographical and institutional distance, instead of proximity, matters for social impact that involves generating educational, societal, and environmental benefits to those outside the UICs. A possible explanation is that complex social challenges require businesses to join forces with new university partners, particularly more research-intensive universities in distant locations. This is a significant contribution, considering the emphasis on universities to generate social value, but the limited understanding of the factors that support this process (de Silva et al., 2021a, 2021b). In that respect, we validate the importance of social value creation through UICs (Rossi and Rosli, 2015; De Jong et al., 2014; Rau et al., 2018) by outlining the need for geographical and institutional distance between universities and businesses in order to generate social impacts. Since universities and businesses are often encouraged to generate social value in their local areas (D'Este and Iammarino, 2010; Hewitt-Dundas, 2013), this finding makes a significant original contribution by questioning the appropriateness of such expectations from local universities and businesses.

Second, we demonstrate that cognitive proximity is not significantly associated with knowledge impact (improving knowledge and competence of businesses as well as teaching- and research-related knowledge of universities). Independently, institutional proximity is found to be important in enabling communication and exchange of knowledge, which is crucial for the production of new knowledge (De Silva and Rossi, 2018; Taheri and van Geenhuizen, 2016). However, cognitive proximity when combined with institutional proximity has a negative effect on knowledge impact: excessive closeness of both norms and routines (i.e., institutional proximity) and knowledge bases (i.e., cognitive proximity) might constrain the novelty that each partner brings to the collaboration, hampering the production of original knowledge.

Next, we found that both geographical and institutional proximity are positively associated with economic impact (improving financial and economic outcomes as well as production process and operations). It is possible that geographical proximity facilitates frequent, face-to-face, close interactions, informal exchange of knowledge, and knowledge spillovers (Boschma, 2005; Salter and Martin, 2001; Iacobucci and Perugini, 2023), leading to economic impacts. In particular, since the generation of economic impact is mainly driven by the needs of business, it is important for the success of the problem-solving activity that the academic partner is familiar with business practices and routines. However, interestingly the interaction between geographical and institutional proximity has a negative effect on economic impact. Perhaps this combination results in excessive familiarity between the partners, leading them to rely heavily on their existing network (Oliver, 2004) which might reduce the UIC's capability to solve pressing and novel business problems.

Finally, we demonstrate an original methodology to operationalise different types of impact of UICs, based on the use of secondary documental sources. This approach has potentially wider application to the analysis of other sets of impact reports, which are increasingly available since public and private funders increasingly require applicants to produce narrative statements describing the expected or actual impact of their projects, to be used for evaluation purposes.

5.2. Practical and policy implications

On practical implications, our study first finds that institutional and cognitive proximity are substitutes in relation to knowledge impact, and this further implies that organisations should choose their partners carefully when their aim from UICs is to improve knowledge and competence of businesses and teaching- and research-related knowledge of universities. Particularly, in order to maximise the production of knowledge impact from the UIC, organisations that frequently collaborate with universities should seek university partners with distant knowledge bases, whereas organisations that are not used to collaborating with universities should seek university partners with close knowledge bases.

Second, our finding that geographical and institutional proximity are substitutes in relation to economic impact, implies that organisations that wish to improve financial and economic outcomes as well as production process and operations should seek closely located academic partners with whom they have not collaborated previously, or alternatively, if they wish to rely on their network of previous collaborations, they should select more geographically distant ones.

Third, by establishing that institutional and geographical distance are associated with social impact, we can suggests that organisations that wish to generate educational, societal, and environmental benefits to those outside the UICs should seek partners that are located at a distance and which have less experience in engaging in UICs.

Next, our study's finding that the type of impact produced is affected by the UIC's amount of funding and subject area and by the seniority of the academic partners, suggests that intended impact needs to be embedded in the UIC from the start (Hessels and van Lente, 2008), through the identification of appropriate partners and sources of funding.

Finally, policy-wise, our study suggests that funders running schemes supporting UICs should encourage potential participants to select their partners carefully based on the types of impact they would like to achieve. For example, if the scheme has the objective of encouraging economic impact, they can impose some restrictions to encourage participants to choose partners that are geographically close or partners that have prior experience of collaborations but not both. Similarly, if the scheme has the objective of encouraging knowledge impact, some restrictions could be imposed to discourage partnerships between organisations that have prior experience of collaborations as well as very close knowledge bases.

5.3. Limitations and future research

Our study's main limitations relate to the size and nature of our sample. In fact, we worked with a relatively small sample of UICs occurring in a specific context (the UK) and within the framework of a specific government-funded programme. Yet, while the KTP scheme prescribes certain aspects of the partnership, the collaborators still maintain a lot of freedom to select their partners, to decide how the UIC is organised and managed, to continue their collaboration after the end of the KTP, and to seek additional funding (Rosli et al., 2018). Moreover, the types of organisations that can be involved in KTPs as 'business partners' are very varied and they include small, medium or larger businesses, not-for-profit organisations as well as public sector organisations. Therefore, we expect that our findings can be generalised to most other UICs, which involve universities and any type of external organisations coming together to deliver a project aligned with the partner organisation's objectives. Still, it would be valuable for future research to investigate similar issues using larger scale datasets, different types of collaboration programmes, and different national and regional contexts.

The finding that proximities interact in complex ways calls for further analyses, in particular, the relationship between proximity and social impact would merit a specific investigation, distinguishing different types of social impacts and unpacking the different types of knowledge underpinning them. Future research could also investigate other forms of proximity such as organisational, social and cultural. Moreover, the effects of the selection of partners with specific characteristics (including proximity) in order to achieve certain types of impact, should be disentangled from the role played by proximity in the development of the UIC. These issues could be addressed through quantitative empirical studies in which it is possible to include sample selection of partners with certain types of proximity. Qualitative studies might also be helpful. The prior experience of the collaborators could be investigated further: for instance, the effect of prior collaborative experience in research may have different influence compared with prior collaborative experience in commercialisation activities.

6. Conclusions

We conclude with a reflection on the implications of our paper for social impact and the effect of interaction among proximities on generating impacts during UICs. Since universities and businesses are often encouraged to generate impacts, there needs to be some strategic thinking around UICs and proximity.

While UICs often generate social value in their local areas, in terms of educational, societal, and environmental benefits to those outside the UICs, our finding that geographical and institutional distance between partners promotes social value creation, suggests that local social value creation is not always facilitated by UICs that involve local businesses working with local universities, and partners that have prior experience of working with each other. Instead, businesses and universities that are geographically distant and have not worked together previously are more likely to offer the required change and innovation for social value creation. Under these circumstances, it is imperative that policy initiatives facilitate and encourage such distant interactions to generate social value. Considering the strengths of government bodies as convenors, they could facilitate UICs by introducing partners with appropriate distances in relation to the generation of social impact (i.e., by promoting UICs where collaborators have some geographical and institutional distance).

For all types of impact, we find that combined proximities tend to hamper impact. For example, the combination of cognitive and institutional proximity is negatively associated with knowledge impact, the combination of geographical and institutional proximity is negatively associated with knowledge impact, and geographical and institutional proximities are negatively associated with social impact. Therefore, there needs to be greater awareness of the importance for UIC participants to include some elements of diversity in their choice of collaborators.

CRediT authorship contribution statement

Federica Rossi: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Muthu De Silva:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Pasquale Pavone:** Writing – review & editing, Methodology, Formal analysis. **Ainurul Rosli:** Writing – review & editing, Investigation, Conceptualization. **Nick K.T. Yip:** Writing – review & editing, Investigation, Conceptualization.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Summary of past research on the effect of proximity on university industry collaborations.

Paper	Context	Influence of Proximity (independent variables)	Core influence (Dependent variable)
Effect of proximity on the probability to collaborate			
Arundel, A. and A. Geuna. 2004. Proximity and the use of public science by innovative European Firms. *Economics of Innovation and New Technology* 13: 559–580.	Europe	Combined effect of geographical proximity, the quality and the significance of public research organisations, and firm's R&D expenditure	on the PROPENSITY of firms to **SOURCE** KNOWLEDGE from public research
Laursen, K., Reichstein, T. and A. Salter. 2011. Exploring the effect of geographical proximity and university quality on university–industry collaboration in the United Kingdom. *Regional Studies* 45(4): 507–523.	United Kingdom	The combined effect of geographical proximity, university quality and firm's absorptive capacity	on firm's propensity to **INITIATE** interaction with a university
D'Este, P., Iammarino, S. and F. Guy. 2013. Shaping the formation of university–industry research collaborations: what type of proximity does really matter? *Journal of Economic Geography* 13 (4): 537–555	United Kingdom	The combined effect of geographical proximity, institutional proximity, the experience of partners, and if a firm is in an industrial cluster	on the **FORMATION** of University-Industry research collaborations

(*continued on next page*)

Table A1 (*continued*)

Paper	Context	Influence of Proximity (independent variables)	Core influence (Dependent variable)
Hewitt-Dundas, N. 2013. The role of proximity in university-business cooperation for innovation. *The Journal of Technology Transfer* 38(2): 93–115.	United Kingdom	The effect of geographical proximity and the quality of the university	on firm's propensity to **INITIATE** interaction with a university
Hong, W. and Y—S. Su. 2013. The effect of institutional proximity in non-local university–industry collaborations: An analysis based on Chinese patent data. *Research Policy* 42(2): 454–464.	China	The combined effect of geographical and institutional proximities	on the probability of **INITIATING** collaboration
De Fuentes, C. and Dutrénit, G. 2012. Best channels of academia–industry interaction for long-term benefit. *Research Policy* 41(9):1666–1682.	Mexico	The combined effects of geographical proximity, knowledge type (codified/tacit), and firm's absorptive capacity	on firm's propensity to **INITIATE** interaction with a university
Crescenzi, R., Filippetti, A. and S. Iammarino. 2017. Academic inventors: collaboration and proximity with industry, *Journal of Technology Transfer* 42(4): 730–762.	Italy	The combined effect of geographical and institutional proximities and the involvement of ‘star inventors’	on the propensity to **INITIATE** university-business interactions
Johnston, A. and R. Huggins. 2017. University-industry links and the determinants of their spatial scope: A study of the knowledge intensive business services sector. *Papers in Regional Science* 96(2): 247–260.	United Kingdom	The combined effect of geographical proximity and characteristics of universities and firms	on **FORMING** university industry linkages
Gomes Santos, E., Garcia, R., Araujo, V., Mascarini, S., Costa, A. 2021. Spatial and non-spatial proximity in university–industry collaboration: Mutual reinforcement and decreasing effects. *Regional Science Policy & Practice* 13(4):1249–1261.	Brazil	The combined effect of the relationship between geograhical and cognitive proximity	on firm's propensity to **INITIATE** interaction with a university
Atta-Owusu, K., Dahl Fitjar, R. and A. Rodríguez-Pose. 2021. What drives university-industry collaboration? Research excellence or firm collaboration strategy? *Technological Forecasting and Social Change*, 173: 121084.	Norway	The combined effect of geographical proximity and characteristics of universities	on firm's propensity to **INITIATE** interaction with a university
Effect of proximity on the collaboration			
Bruneel J., D'Este P. and A. Salter. 2010. Investigating the factors that diminish the barriers to university–industry collaboration. *Research Policy* 39(7): 858–868.	United Kingdom	The effect of organisational proximity on	on **LOWERING BARRIERS** for university-industry interactions
D'Este, P. and S. Iammarino. 2010. The spatial profile of university-business research partnerships. *Papers in regional science* 89(2): 335–350.	United Kingdom	The combined effect of research quality and geographical proximity	on the **INTENSITY** of university-industry collaborations
Muscio, A. and A. Pozzali. 2013. The effects of cognitive distance in university-industry collaborations: some evidence from Italian universities. *The Journal of Technology Transfer* 38(4): 486–508.	Italy	Effect of cognitive proximity	on **FREQUENCY** of university industry collaboration
Effect of proximity on the collaboration's output			
Abramovsky, L., Harrison, R. and H. Simpson. 2007. University research and the location of business R&D. *Economic Journal* 117 (3), 114–141.	United Kingdom	The effect of geographical proximity of universities to the pharmaceuticals R&D companies	on the **QUALITY** of university research..
Ponds, R., Van Oort, F. and K. Frenken. 2007. The geographical and institutional proximity of scientific collaboration networks. *Papers in Regional Science* 86(3): 423–443.	Netherlands	The combined effect of geographical and institutional proximity	on the probability to **CO-PUBLISH** by universities, firms and other organisations.
Østergaard, C. R. and I. Drejer. 2021. Keeping together: Which factors characterise persistent university–industry collaboration on innovation? *Technovation.*	Denmark	The effect of geographical proximity and of firm characteristics	On the **CONTINUATION** of university-industry collaborations.

Interview questions

Description of the KTP and the informant's involvement in it:

- Can you describe the objectives of the KTP?
- How did you get involved in the project?
- Who were the other parties involved?
- Were the objectives of the KTP reached?
- Why was the KTP used as the mechanism to solve the problem?

Description of the KTP's impacts (immediate and emergent ones):

- How did you benefit from the KTP?
- What is your perception of the overall impact of the KTP?
- In particular, are you aware of any long-term impacts of the KTPs, and/or of unexpected outcomes that had not been envisaged at the start of the project?
- Have any further collaboration emerged after the KTPs?
- With the same partners?
- With different partners?

Determinants of these impacts:

- What worked well in this project?
- What did not work so well / what were the main challenges that you encountered?
- Would you be able to share some good practices from this KTP that may be beneficial for others to know?

Specificities of KTPs in the social sciences

- Do you have experience of science-based KTPs? If so, what do you think were their main differences with respect to this social science-based KTP?
- Has this KTP led to other projects in the same discipline / area?
- What do you think the specific contribution of the KTP was?
- How would you measure/assess this contribution?
- How do you think the contribution of KTPs in the social sciences differ from the contributions of science-based projects?
- If you were to do another KTP, what would it be about?

Methodology used to identify impact themes

The automatic analysis of textual data, aimed at both qualitative and quantitative analysis of content, properties, and characteristics, allows for more than just reading a text; it enables the representation of information in a distinct manner. These methods provide an ideal framework for employing Text Mining tools. Text Mining, a continually expanding multidisciplinary research field, amalgamates various tools from Computational Linguistics, Information Retrieval, and Statistics. Its primary objective is to extract valuable information from a set of textual entities (namely, a *Corpus*) (Aggarwal and Zhai, 2012; Berry, 2004; Berry and Kogan, 2010; Feldman and Sanger, 2007; Sullivan, 2001; Weiss, 2010).

Among the numerous objectives that can be defined in text analysis, the identification of topics emerges as one of the primary analyses conducted. In recent years, several methods for identifying topics in a *corpus* have been developed, with the most prominent ones categorised into three main groups: probabilistic methods, matrix factorisations, and clustering techniques.

Recognising that there is no single method considered universally superior (Alboni et al., 2023), and that each analytical strategy must adapt to the specific characteristics of the analysed corpus, we have opted for the identification of topics using the Louvain community detection algorithm (Blondel et al., 2008). This algorithm is applied to a network analysis (Carley, 2020; Popping, 1999) conducted on a $\langle terms \times terms \rangle$ matrix. Community detection can be viewed as a hard clustering approach, as the concepts do not overlap, and each term exhibits a strong membership to a single concept. It enables the automatic determination of the partition. In contrast, for other popular methods, it is necessary to set the number of topics to be identified a priori.

Words serve diverse functions within a sentence, including language structure roles (articles, prepositions, conjunctions, etc.) and semantic content roles. Among the latter, we can find terms describing and qualifying objects and events (common nouns and adjectives); indicating actions (verbs); denoting places (toponyms), and finally, those signifying proper nouns.

Text mining strategy

To ensure the highlighting of relevant topics in the examined corpus, pre-processing of the text becomes imperative. To achieve this, a text mining strategy was formulated. The initial step involved analysing the texts by structuring the textual information in a lexical and textual database, utilising TaLTaC2.[13] software (Bolasco, 2010; Bolasco and De Gasperis, 2017). With the objective of identifying topics in the *corpus*, the process involves mining the text to extract only "terms" with semantic meaning. Consequently, the unstructured textual information is organised within a Document Warehouse, comprising the Vocabulary DB (lexical units of analysis) and the Documents DB (textual units of analysis). Through part-of-speech (POS) tagging on vocabulary words, we define the grammatical categories of words and their corresponding lemmas.

POS tagging holds significant importance in this context as it enables a series of steps to reduce the number of words under analysis and select only terms of semantic content. By applying POS tagging, we can designate the lemmas of words as units of analysis, leading to the elimination of inflections (e.g., singular/plural forms). Additionally, POS tagging allows us to selectively choose the lemmas considered useful for analysis, distinguishing them as active lemmas, in contrast to supplementary lemmas.

In this context, we categorise as active elements of the analysis all lemmas annotated as adjectives and nouns. Nouns, in particular, represent the objects and subjects of texts, constituting the central element of the message conveyed by a text. Finally, POS tagging aids in identifying multiword expression nouns through the application of a lexical-textual model (Bolasco and Pavone, 2010; Pavone, 2018, 2010) and the exploration of their syntactic structures. Multiword expressions (MWEs) are compound lexical units larger than a word, capable of embodying both idiomatic and compositional meanings. The identification of recurrent MWE allows us to take into account the context in which individual words are embedded. The following table lists the 50 most frequently occurring multi-words, of the 1824 identified. After completing this step, the set of texts to be analysed included 16,013 different words for a total of 381,141 occurrences.

Table A2
List of the 50 most frequently occurring multi-words.

Progressive n.	Multi-words	Occurrences
1	Knowledge transfer partnerships	815
2	Technology strategy board	715
3	Academic partner	597
4	New knowledge	476
5	Accelerating business	426
6	Business relevance	409
7	Professional development opportunities	401
8	Research organisations	400
9	Gain business-based experience	398
10	Knowledge transfer partnership	389
11	Economic growth	284
12	Quality of life	282
13	Business-led organisation	279
14	Benefit of uk	279
15	Lead academic	223

(*continued on next page*)

[13] www.taltac.com

Table A2 (*continued*)

Progressive n.	Multi-words	Occurrences
16	Project management	213
17	Product development	210
18	New market	203
19	Managing director	172
20	New business	169
21	New product	272
22	Greater understanding	139
23	Sales turnover	128
24	Professional development	120
25	Competitive position	118
26	Annual sales turnover	105
27	Product range	103
28	Business school	101
29	Knowledge transfer	100
30	Academic supervisor	96
31	New research	91
32	Product design	89
33	Marketing strategy	86
34	Research opportunities	86
35	Wide range	73
36	School of engineering	72
37	Project management skills	69
38	Valuable experience	69
39	Cost savings	68
40	Annual profit	68
41	Management skills	66
42	Career development	65
43	Both associates	65
44	Teaching material	65
45	Increased knowledge	64
46	Information system	64
47	Successful collaboration	63
48	Technical skills	63
49	Competitive edge	61
50	Business processes	61

In the pursuit of identifying the prevalent topics in the corpus in the subsequent stages of the analysis with which to construct a vector space model for subsequent analysis stages, only terms (including lemmas and Multiword Expressions - MWEs) categorised as nouns and adjectives are selected, setting a threshold of five occurrences.

Through vector space model representation, the textual data are transformed into numerical vectors and then into matrices, which can be analysed to bring out structural semantic similarities within the documents. Therefore, for each *Corpus* the records (priorities) are represented as: vectors of codes count and vectors of terms count, in a multidimensional space. The sparse matrixes obtained, ⟨documents ×selected terms⟩, represent new information on which to elaborate statistical analysis. One of the limitations of the vector space model is its disregard for the context in which terms are employed. To partially recover both structural and semantic information, a ⟨terms ×terms⟩ co-occurrence table can be constructed.

Graph Network analysis and topic detection.

The second step consisted in identifying the impact themes present in the texts by means of topic detection. In particular, we constructed a set of dictionaries (collections of words) capturing different dimensions of impact, using similarity analysis (Flament, 1962; Flament, 1981; Marchand and Ratinaud, 2012) performed with Iramuteq[14] and Gephi.[15] This approach identifies communities of words based on a co-occurrence matrix whose generic term contains the number of co-occurrences between each pair of words (how many times these words appear next to each other in the fragments of texts).[16] This matrix is used to produce a graph linking each word (node) with those with which there is greater co-occurrence within sentences contained in the documents. We then identify communities of nodes[17] (Girvan and Newman, 2002; Fortunato and Hric, 2016), that is, densely inter-connected subgraphs that are sparsely connected to other parts of the network (Wasserman and Faust, 1994). These non-overlapping communities of nodes represent sets of words that occur together frequently, and which can be used as thematic dictionaries.[18]

This analysis[19] produced 44 communities, or dictionaries which were balanced in terms of numbers of nodes and links. The 44 dictionaries ranged in size from 294 to 8, with a mean of 90.5 and a standard deviation of 70.1. Since small dictionaries are not very informative, we focused on the 16 dictionaries which contained 100 words or more.

[14] R interface for Multidimensional Text and Questionnaire Analysis. Free software built with open source software. 2009–2020 Ratinaud. http://www.iramuteq.org

[15] www.gephi.org (Bastian et al., 2009)

[16] The length of a fragment is a sentence or at most 40 words.

[17] We used the Louvain method (Blondel et al., 2008) available in the Gephi software.

[18] The words that make up each dictionary are disjointed, meaning that it is not possible to have the exact same word in more than one dictionary.

[19] Our initial analysis using the overall set of words in the documents led to the identification of a few very frequently occurring words (six words, each accounting for >1 % of all the occurrences in the document collection, and together accounting for 11.5 %), which gave rise to six communities around each one of these words, plus a lot of other small communities containing more isolated words. The communities generated by each of these six words were very large and heterogeneous and did not have a specific impact connotation as the six words were very generic (“KTP”, “project”, “associate”, “company”, “research”, “university”). In order to identify more balanced communities, we therefore eliminated these six most frequently occurring words and focused only on the others. Six words is the minimum amount of words that can be dropped while generating a manageable amount of communities that are quite balanced in size.

We then carefully inspected the words included in each dictionary, in order to label them according to their overarching themes. As the dictionaries include closely related terms based on their usage in the texts, this identifies some degree of conceptual homogeneity. Interpreting the meaning of each dictionary – in our case, in terms of impact types – requires an expert reading of the list of words, where each word is interpreted in the context of its relationships with the other words in the dictionary, to define, wherever possible, the semantic trait of each dictionary (Griffiths et al., 2007).

Visual inspection suggested that 7 of these dictionaries contained lists of words that could be associated with the impact of the UIC.[20] In the following table, we list the 7 'impact dictionaries', and we arrange them according to the three main impact dimensions emerging from the literature – knowledge, economic, social.

Table A3
Impact dictionaries identified through similarity analysis.

Impact type	Label of dictionary	Number of words in dictionary	Examples of words most frequently occurring within dictionary
Knowledge impact on knowledge intensive activities of business and university	Organisational information	201	Developed, data, future, innovative, successfully, analysis, integrated, implemented, model, communication, culture, long, impact, prototype, framework, planned, portfolio, standard
	Organisational competences	148	Knowledge, skill, enhanced, profile, reputation, acquired, applied, embedded, specific, enhancing, managing, smes, information_system, advantage, base, market position, accreditation, community
	Teaching and research	121	Case, material, study, studies, industrial, students, generated, papers, courses, relevant, published, partners, modules, research_opportunitiy, conference, undergraduate, teaching_material, university_staff, teaching_material
Economic impact on operational activities of business	Financial and economic outcomes	102	Increase, sale, expected, profit, turnover, sales_turnover, completion, profit, new_markets, annual_sales_turnover, rise, anticipated, resulting, profitability, due, market_share, tax, annual_profit
	Production process / operations	294	Design, led, process, manufacturing, technique, product_development, service, introduced, applications, current, capability, manufacture, advanced, testing, modelling, computer, equipment, focus, consultancy
Social impact on external stakeholders	Society and, environment	106	including, people, health, environment, number, education, food, built, responsible, water, scotland, life, safety, north, air, works, transport, wales, rural_affairs
	Education	151	management, level, nvq, achieved, phd, professional, msc, institute, role, completed, manager, business_school, degree, membership, awarded, mphil, member, complete, progressed

The TF-IDF index

Formally, the TF-IDF index is built as follows. Let *t* be the term and *d* the document (in our case, the report) for which the index is computed. *tF(t, d)* is the frequency of *t* in *d*. This term is then divided by the inverse document frequency *idf(t)*, which is defined as:

$$\mathrm{idf}(t) = log\frac{|D|}{1 + |\{d : t \in d\}|}$$

where $|\{d : t \in d\}|$ is the number of documents where t appears, when the term-frequency function satisfies $\mathrm{tf}(t, d) \neq 0$ (1 is added to the formula to avoid zero-division). This term measures how rare that dictionary is in the collection *D* (the fewer the number of documents *d* in which *t* appears compared to the overall number of documents in the collection *D*, the higher is *idf*). Hence:

$$\text{tf-idf}(t) = \mathrm{tf}(t, d) \times \mathrm{idf}(t)$$

This formula has an important consequence: a high weight of the TF-IDF calculation is reached when there is a high term frequency (*tf*) in the given document (local parameter) and a low document frequency of the term in the whole collection (global parameter). The TF-IDF index for a dictionary of words is computed as the sum of the normalised TF-IDF indices of each word in that dictionary.[21] In general, TF-IDF has a dual function, depending on the context of the analysis and the objective. In the lexical analysis context, TF-IDF is used to weigh words proportionally to their relative frequency and according to their ability to discriminate groups of documents. In this way, when a word is very frequent and it is present in many documents, the value of TF is low (stop-words and non-relevant terms filtering), while when it is present in few documents its weight is higher (Salton and Yu, 1975). Its use in textual analysis allows to rank a document's relevance given a query, weighting the documents against the elements of textual queries providing a measure of relevance of the documents. The retrieval effectiveness depends on two main factors: items relevant to the query must be retrieved; extraneous items must be rejected. The two measures used to assess a weighting system are recall and precision. Recall is the portion of relevant items retrieved, precision is the portion of retrieved items that are relevant. Terms that are frequently mentioned in individual documents, represent the recall devices. TF factor alone cannot ensure acceptable retrieval performance. Specifically, when the high frequency terms are not concentrated in a few documents tend to be retrieved, and this affects the search precision. The IDF factor performs this function. Terms discrimination consideration suggest that the best terms for document content identification should have high TF but low overall collection frequencies (Salton and Buckley, 1988).

[20] The remaining 9 dictionaries contained sets of words that either related to the functioning and management of the UIC, rather than to its impact, or that were difficult to classify under a single conceptual category.

[21] The value of TF-IDF used in our study is a value on which different normalisations are previously applied. First of all, the TF-IDF is normalised with respect to the highest value of the occurrence present in the document. Furthermore, the TF-IDF value of a word in the document is normalised with respect to the sum of the TF-IDF values of all the words in the document so that documents of various sizes can be compared. Finally the TF-IDF score of the dictionary is divided by the theoretical maximum value of TF-IDF that could be reached in the collection. This way, the TF-IDF score is normalised between zero and one.

Table A4
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
2	−0.01	1.00																					
3	0.02	−0.02	1.00																				
4	0.11	−0.05	0.17	1.00																			
5	0.04	−0.12	0.04	0.13	1.00																		
6	0.04	−0.08	−0.09	−0.04	0.02	1.00																	
7	0.01	0.07	−0.12	−0.16	−0.06	0.01	1.00																
8	−0.07	0.25	0.17	0.20	−0.09	0.04	0.01	1.00															
9	0.03	0.22	0.06	0.08	0.10	0.01	0.04	0.35	1.00														
10	0.04	−0.13	0.01	−0.03	0.06	−0.08	0.01	−0.12	−0.08	1.00													
11	0.15	−0.08	0.18	0.18	−0.14	0.02	−0.08	−0.02	0.04	0.15	1.00												
12	−0.02	0.18	−0.15	0.02	0.10	−0.06	0.02	0.03	0.09	0.04	−0.24	1.00											
13	0.09	0.21	−0.03	0.15	−0.10	0.00	−0.06	0.01	0.02	0.03	−0.01	0.30	1.00										
14	0.00	−0.05	0.14	0.07	0.01	0.06	0.00	0.01	0.01	0.04	0.00	−0.15	−0.41	1.00									
15	−0.11	−0.17	−0.05	−0.16	0.00	0.01	0.06	0.00	−0.05	−0.01	0.01	−0.17	−0.44	−0.46	1.00								
16	−0.07	−0.19	0.10	−0.18	0.10	0.03	0.01	0.00	−0.05	0.03	−0.08	−0.17	−0.22	0.07	0.23	1.00							
17	0.10	0.10	−0.24	0.13	0.24	−0.06	0.03	0.00	0.11	0.00	−0.04	0.27	0.13	−0.14	−0.18	−0.39	1.00						
18	−0.04	0.01	0.13	0.05	−0.16	0.01	−0.06	0.00	−0.06	−0.03	0.08	−0.15	−0.06	0.11	0.04	−0.33	−0.42	1.00					
19	0.03	0.05	0.03	0.02	−0.30	−0.08	0.01	−0.01	−0.04	0.02	0.07	0.00	0.20	−0.06	−0.11	−0.21	−0.27	−0.23	1.00				
20	0.00	0.07	0.01	0.00	−0.02	−0.02	−0.08	0.06	0.04	−0.02	−0.02	0.05	0.05	−0.06	0.04	−0.05	−0.02	0.05	−0.04	1.00			
21	−0.06	−0.28	0.04	−0.07	0.20	0.11	−0.02	−0.03	−0.08	0.04	0.00	−0.20	−0.42	0.18	0.26	0.26	−0.23	−0.04	−0.03	−0.12	1.00		
22	−0.08	−0.01	0.17	0.02	−0.08	0.10	0.11	0.02	0.04	0.00	0.07	−0.03	−0.04	0.01	0.02	−0.04	−0.06	0.16	−0.05	−0.02	−0.26	1.00	
23	−0.06	0.23	−0.04	−0.03	−0.12	−0.06	0.10	0.06	0.08	−0.04	−0.06	−0.04	−0.08	0.06	−0.03	−0.03	0.08	−0.02	−0.03	−0.02	−0.28	−0.05	1.00
24	0.13	0.18	−0.11	0.08	−0.11	0.01	−0.06	−0.02	0.02	−0.02	0.00	0.24	0.50	−0.21	−0.28	−0.24	0.24	−0.03	0.08	−0.07	−0.79	−0.15	−0.16

Note to correlation matrix:

1	Knowledge impact	13	Organisational
2	Social impact	14	Process
3	Economic impact	15	Product
4	Geographical proximity	16	Firm high tech manufacturing
5	Institutional proximity	17	Firm KIS
6	Cognitive proximity	18	Firm other manufacturing
7	Senior academic	19	Firm other services
8	Local funder	20	Agriculture
9	N funding bodies	21	Technology
10	Grant amount	22	Humanities
11	SME	23	Medical
12	Non profit	24	Social sciences

Table A5
Model significance.

	Model (1)			Model (2)			Model (3)		
	Statistic	F	Prob>F	Statistic	F	Prob>F	Statistic	F	Prob>F
W	0.5273	4.03	0.0000	0.5229	3.91	0.0000	0.4789	3.39	0.0000
P	0.5638	3.93	0.0000	0.5706	3.82	0.0000	0.6497	3.30	0.0000
L	0.7325	4.12	0.0000	0.7432	3.99	0.0000	0.8839	3.49	0.0000
R	0.4043	6.87	0.0000	0.4061	6.60	0.0000	0.5014	5.98	0.0000
Residual	391			390			382		

Note to Table A3: Number of observations: 415. W = Wilks' lambda; L = Lawley-Hotelling trace; P = Pillai's trace; R = Roy's largest root.

Robustness check: regression with instrumental variables

Appropriate instrumental variables should be correlated with the instrumented regressors but not with the independent variables, hence, we sought to include variables which were likely to influence the collaborators' proximity but not the impact of the UIC. For geographical proximity, we chose a binary variable (*Govt_funding*) equal to 1 if the project received funding from a government department, and zero otherwise. The rationale for this choice is that, given that the UK government in recent years has promoted a broad agenda to promote local development, universities applying for KTP funding from a government department might have been encouraged to select a geographically close business partner to demonstrate alignment with government priorities. For institutional proximity, we used the project's duration expressed in months (*Duration*) since we expect longer projects to be more complex and therefore to require greater initial alignment between the partners' norms and routines, to be able to collaborate effectively. For cognitive proximity, we used a binary variable (*Monodisciplinary*) equal to 1 if the KTP's knowledge transfer area and the KTP's technology were the same, and 0 if they were different (both variables - KTP's knowledge transfer area and KTP technology – are available from the KTP database). The idea is that the closer match there is between the knowledge transferred in course of the KTP and the technology that is the focus of the KTP, the closer the cognitive alignment required between the collaborators. At the same time, we do not expect any of the three instruments to directly influence the type of impact of the KTP. Since this model includes interaction effects, we included interactions between the instruments in the first stage regressions. The Durbin-Watson statistics are significant, rejecting the null hypothesis of exogeneity of the regressors, and indicating that an instrumental variables approach is appropriate. The Sargan and Barmann statistics are not significant, suggesting that the null hypothesis of the exogeneity of the instruments can be accepted.

Table A6
Instrumental variables regressions.

	Model 2 with instrumental variables		
	(a)	(b)	(c)
Variables	Knowledge impact	Economic impact	Social impact
Geographical proximity	1.255	1.204	−0.165
	(0.347)	(0.320)	(0.304)
Institutional proximity	0.904**	0.593**	−0.271
	(0.363)	(0.334)	(0.318)
Cognitive proximity	0.657*	1.244	−0.517*
	(0.331)	(0.305)	(0.290)
Cognitive*geographic	0.024	0.030	0.112
	(0.117)	(0.108)	(0.102)
Institutional*geographic	−0.106	−0.073	−0.158*
	(0.094)	(0.087)	(0.083)
Cognitive*institutional	−0.260**	−0.168*	0.146
	(0.107)	(0.099)	(0.094)
Senior_academic	0.166	−0.221**	0.088
	(0.111)	(0.102)	(0.097)
Local_funder	−0.257	0.584***	0.878***
	(0.215)	(0.198)	(0.188)
N_funding_bodies	0.532	0.051	0.352

(continued on next page)

Table A6 (*continued*)

Variables	Model 2 with instrumental variables (a) Knowledge impact	(b) Economic impact	(c) Social impact
	(0.125)	(0.115)	(0.109)
Grant_amount	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)
SME	0.429**	0.340**	−0.097
	(0.150)	(0.138)	(0.131)
Non_profit	−0.191	−0.246	0.315*
	(0.205)	(0.189)	(0.180)
Organisational	0.001	0.019	0.217
	(0.220)	(0.203)	(0.193)
Process	−0.052	0.070	−0.026
	(0.217)	(0.200)	(0.190)
Product	−0.221	−0.228	−0.205
	(0.215)	(0.198)	(0.188)
Firm high tech manufacturing	0.268	0.101	−0.486
	(0.280)	(0.258)	(0.245)
Firm KIS	0.311	−0.529*	−0.249
	(0.281)	(0.258)	(0.246)
Firm other manufacturing	0.211	−0.065	−0.155
	(0.281)	(0.259)	(0.246)
Firm other services	0.349	−0.139	−0.196
	(0.304)	(0.280)	(0.266)
Agriculture	0.191	0.180	0.337
	(0.554)	(0.510)	(0.485)
Technology	−0.238*	0.090	−0.291
	(0.142)	(0.131)	(0.124)
Humanities	−0.581**	0.907***	−0.283
	(0.274)	(0.252)	(0.239)
Medical	−0.464*	−0.009	0.830
	(0.259)	(0.238)	(0.226)
Constant	−2.780***	−1.400	1.568*
	(0.019)	(0.938)	(0.892)
Observations	415	415	415
R-squared	0.0877	0.1904	0.2832
Wald chi2(23)	44.46	92.98	165.04
P-value	0.004	0.000	0.000

The outcomes of this model are substantially aligned with those of the full model presented in Table 8. In the case of knowledge impact, institutional proximity has a significantly positive effect (and so does cognitive proximity) but the interaction between institutional and cognitive proximity has a significantly negative effect. In the case of knowledge impact, institutional proximity has a significantly positive effect, but the interactions between institutional and geographic and between institutional and cognitive proximities have negative effects (only the latter is significant, however). In the case of social impact, all proximity variables have negative coefficients (in the case of cognitive proximity, the coefficient is significant) and the interaction between institutional and geographic proximities has a significantly negative effect.

References

Aggarwal, C.C., Zhai, C., 2012. Mining text data (Springer Science & Business Media).

Aksoy, A.Y., Pulizzotto, D., Beaudry, C. 2022. University-Industry partnerships in the smart specialisation era., *Technological Forecasting and Social Change* 176, doi:https://doi.org/10.1016/j.techfore.2021.121438.

Albert, M., Laberge, S., McGuire, W., 2012. Criteria for assessing quality in academic research: the views of biomedical scientists, clinical scientists and social scientists. High. Educ. 64, 661–676.

Alboni, F., Pavone, P., Russo, M., 2023. The search for topics related to electric mobility: a comparative analysis of some of the most widely used methods in the literature. METRON 1–25.

Alpaydın, U., Dahl Fitjar, R., 2021. Proximity across the distant worlds of university–industry collaborations. Papers in Regional Science 100 (3), 689–712.

Amabile, T.M., Patterson, C., Mueller, J., Wojcik, T., Odomirok, P.W., Marsh, M., Kramer, S.J., 2001. Academic-practitioner collaboration in management research: a case of cross-profession collaboration. Acad. Manage. J. 44 (2), 418–431.

Ankrah, S., Al-Tabbaa, O., 2015. Universities-industry collaboration: a systematic review. Scandinavian Journal of Management 31, 387–408.

Asheim, B.T., Coenen, L., 2005. Knowledge bases and regional innovation systems: comparing Nordic clusters. Research Policy 34 (8), 1173–1190.

Asheim, B.T., Gertler, M., 2005. The geography of innovation: regional innovation systems. In: Fagerberg, J., Mowery, D., Nelson, R. (Eds.), The Oxford handbook of innovation. Oxford University Press, Oxford, pp. 291–317. Chapter 11.

Aslesen, H., Isaksen, A., 2010. Knowledge-intensive business services as knowledge mediators in different regional contexts: the case of Norway. In: Doloreux, D., Freel, M., Sheamur, R. (Eds.), Knowledge-intensive business services: geography and innovation. Farnham, Ashgate, pp. 99–122. Chapter 5.

Audretsch, D., Keilbach, M.C., Lehmann, E.E., 2006. Entrepreneurship and Economic Growth. Oxford University Press, Oxford.

Backhaus, C., Pitsis, T., Evanschitzky, H., Jankkola, M., 2017. Exploring antecedents of impact in business and management: an analysis of structural characteristics of successful UK REF studies. Academy of Management Conference 2017.

Barnes, T., Pashby, I., Gibbons, A., 2002. Effective university–industry interaction: a multi-case evaluation of collaborative R&D projects. Eur. Manag. J. 20 (3), 272–285.

Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: An Open Source Software for Exploring and Manipulating Networks (International AAAI Conference on Weblogs and Social Media).

Becker, W., Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. Research Policy 33 (2), 209–223.

Bekkers, R., Bodas Freitas, I., 2008. Analysing preferences for knowledge transfer channels between universities and industry: to what degree do sectors also matter? Research Policy 37, 1837–1853.

Berry, M.W., 2004. Survey of text mining. Comput. Rev. 45, 548.

Berry, M.W., Kogan, J., 2010. Text Mining: Applications and Theory. John Wiley & Sons.

Bertello, A., Bogers, M.L., De Bernardi, P., 2022. Open innovation in the face of the COVID-19 grand challenge: insights from the pan-european hackathon 'euvsvirus'. R&D Manag. 52, 178–192.

Blondel V.D., Guillaume J.L., Lambiotte R., Lefebvre, E. 2008. Fast unfolding of communities in large networks. Journal of Statistical Mechanics Theory and Experiment arXiv:0803.0476.

Boardman, P.C., Bozeman, B., 2015. Academic faculty as intellectual property in university–industry research alliances. Econ. Innov. New Technol. 24, 403–420.

Bolasco, S., 2010. TaLTaC 2.10: sviluppi, esperienze ed elementi essenziali di analisi automatica dei testi. LED, Milano.

Bolasco, S., De Gasperis, G., 2017. Taltac 3.0 a web multilevel platform for textual big data in the social sciences. In: Data Science and Social Research – Epistemology, Methods, Technology and Applications. C. Lauro, E. Amaturo, M.G. Grassia, B. Aragona and M. Marino. Springer Publ, pp. 97–103.
Bolasco, S., Pavone, P., 2010. Automatic dictionary-and rule-based systems for extracting information from text, in: Data Analysis and Classification. Springer, pp. 189–198.
Bornmann, L., 2013. What is societal impact of research and how can it be assessed? A literature survey. J. Am. Soc. Inf. Sci. Technol. 64 (2), 217–233.
Boschma, R., 2005. Proximity and innovation: a critical assessment. Regional Studies 39, 61–74.
Bouty, I., 2000. Interpersonal and interaction influences on informal resource exchanges between R&D researchers across organizational boundaries. Acad. Manage. J. 43 (1), 50–65.
Bozeman, B., 2000. Technology transfer and public policy: a review of research and theory. Research Policy 29 (4–5), 627–655.
Bozeman, B., Fay, D., Slade, C.P., 2013. Research collaboration in universities and academic entrepreneurship: the-state-of-the-art. J. Technol. Transfer. 38, 1–67.
Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qual. Res. Psychol. 3 (2), 77–101.
Brown, J.S., Duguid, P., 1998. Organizing knowledge. Calif. Manage. Rev. 40 (3), 90–111.
Bruneel, J., D'Este, P., Salter, A., 2010. Investigating the factors that diminish the barriers to university–industry collaboration. Research Policy 39 (7), 858–868.
Brusoni, S., Prencipe, A., Pavitt, K., 2001. Knowledge specialization, organizational coupling, and the boundaries of the firm: why do firms know more than they make? Adm. Sci. Q. 46 (4), 597–621.
Carley, K.M., 2020. Network text analysis: The network position of concepts, in: Text Analysis for the Social Sciences. Routledge, pp. 79–100.
Chesbrough, H., Lettl, C., Ritter, T., 2018. Value creation and value capture in open innovation. Journal of Product Innovation Management 35 (6), 930–938.
Compagnucci, L., Spigarelli, F. 2020. The Third Mission of the university: A systematic literature review on potentials and constraints. *Technological Forecasting and Social Change* 161.
Coussement, K., Debaere, S., De Ruyck, T., 2017. Inferior member participation identification in innovation communities: the signaling role of linguistic style use. Journal of Product Innovation Management 34 (5), 565–579.
Cowan, R., David, P., Foray, D., 2000. The explicit economics of knowledge codification and tacitness. Industrial and Corporate Change 9, 211–253.
Crescenzi, R., Filippetti, A., Iammarino, S., 2017. Academic inventors: collaboration and proximity with industry. Journal of Technology Transfer 42 (4), 730–762.
Crossick, G., 2009. So who now believes in the transfer of widgets? In Knowledge Future Conference, Warden of Goldsmiths, University of London, October 16–17, 2009.
Cunliffe, A.L., Scaratti, G., 2017. Embedding impact in engaged research: developing socially useful knowledge through dialogical sensemaking. Br. J. Manag. 28 (1), 29–44.
Davids, M., Frenken, S., 2018. Proximity, knowledge base and the innovation process: towards an integrated framework. Regional Studies 52 (1), 23–34.
De Jong, S., Barker, K., Cox, D., Sveinsdottir, T. van de Besselaar, P., 2014. Understanding societal impact through productive interactions: ICT research as a case. Research Evaluation 23 (2), 89–102.
De Silva, M., 2016. Academic entrepreneurship and traditional academic duties: synergy or rivalry? Stud. High. Educ. 41 (12), 2169–2183.
De Silva, M., Rossi, F., 2018. The effect of`firms' relational capabilities on knowledge acquisition and co-creation with universities. Technological Forecasting and Social Change 133, 72–84.
De Silva, M., Wright, M., 2019. Entrepreneurial co-creation: societal impact through open innovation. R&D Management Journal 49 (3), 318–342.
De Silva, M., Howells, J., Meyer, M., 2018. Innovation intermediaries and collaboration: knowledge–based practices and internal value creation. Research Policy 47 (1), 70–87.
De Silva, M., Khan, Z., Vorley, T., Zeng, J., 2019. Transcending the pyramid: opportunity co-creation for social innovation. Ind. Mark. Manag.
De Silva, M., Gokhberg, L., Meissner, D., Russo, M., 2021a. Addressing societal challenges through the simultaneous generation of social and business values: a conceptual framework for science-based co-creation. Technovation 104, 102268.
De Silva, M., Rossi, F., Yip, N.K., Rosli, A., 2021b. Does affective evaluation matter for the success of university-industry collaborations? A sentiment analysis of university-industry collaborative project reports. Technological Forecasting and Social Change 163, 120473.
De Silva, M., Al-Tabbaa, O., Pinto, J., 2023. Academics engaging in knowledge transfer and co-creation: push causation and pull effectuation? Research Policy 52 (2), 104668.
D'Este, P., Iammarino, S., 2010. The spatial profile of university-business research partnerships. Pap. Reg. Sci. 89 (2), 335–350.
D'Este, P., Iammarino, S., Guy, F., 2013. Shaping the formation of university–industry research collaborations: what type of proximity does really matter? J. Econ. Geogr. 13 (4), 537–555.
Dolfsma, W., van der Eijk, R., 2016. Distances in organizations: innovation in an R&D lab. British Journal of Management 27 (2), 271–286.
Dupire, M., M'Zali, B., 2018. CSR strategies in response to competitive pressures. J. Bus. Ethics 148, 603–623.
Ernst, D., Bamford, J., 2005. Your alliances are too stable. Harv. Bus. Rev. 83 (6), 133–141.
Fassio, C., Geuna, A., Rossi, F., 2019. Which governance of university-industry interactions increases the value of industrial inventions? Ind. Corp. Chang. 28 (5), 1227–1256.
Feldman, R., Sanger, J., 2007. The text mining handbook: Advanced approaches in analyzing unstructured data. In: Cambridge University Press, Cambridge. York, New.
Fernald, K., Pennings, E., Claassen, E., 2015. Biotechnology commercialization strategies: risk and return in interfirm cooperation. Journal of Product Innovation Management 32 (6), 971–996.
Flament, C., 1962. L'analyse de similitude. Cah. Cent. Rech. Opérationnelle 63–97.
Flament, C. 1981 L'analyse de similitude, une technique pour les recherches sur les représentations sociales. *Cah. Psychol. Cogn.* 375–395.
Fortunato, S., Hric, D., 2016. Community detection in networks: a user guide. Phys. Rep. 659, 1–44.
George, G., Zahra, S.A., Wood, D.R., 2002. The effects of business-university alliances on innovative output and financial performance: a study of publicly traded biotechnology companies. J. Bus. Ventur. 17 (6), 577–609.
Geuna, A., Martin, B.R., 2003. University research evaluation and funding: an international comparison. Minerva 41 (4), 277–304.
Girvan, M., Newman, M.E.J., 2002. Community structure in social and biological networks. PNAS 99 (12), 7821–7826.
Giuliani, E., Arza, V., 2009. What drives the formation of 'valuable' university–industry linkages? Insights from the wine industry. Research Policy 38, 906–921.
Giuliani, E., Bell, M., 2005. The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. Research Policy 34, 47–68.
Gomes Santos, E., Garcia, R., Araujo, V., Mascarini, S., Costa, A., 2021. Spatial and non-spatial proximity in university–industry collaboration: mutual reinforcement and decreasing effects. Reg. Sci. Policy Pract. 13 (4), 1249–1261.
Griffiths, T.L., Steyvers, M., Tenenbaum, J.B., 2007. Topics in semantic representation. Psychol. Rev. 114, 211–244.
Hannigan, T.R., Haans, R.F.J., Vakili, K., Tchalian, H., Glaser, V.L., Wang, M.S., Jennings, P.D., 2019. Modelling in management research: rendering new theory from textual data. Acad. Manag. Ann. 13 (2), 586–632.
Herstad, S.J., Aslesen, H.W., Ebersberger, B., 2014. On industrial knowledge bases, commercial opportunities and global innovation network linkages. Research Policy 43 (3), 495–504.
Hessels, L.K., Van Lente, H., 2008. Re-thinking new knowledge production: a literature review and a research agenda. Research Policy 37 (4), 740–760.
Hewitt-Dundas, N., 2013. The role of proximity in university-business cooperation for innovation. The Journal of Technology Transfer 38 (2), 93–115.
Heylen, L., Mortelmans, D., Boudiny, K., Herman, M., 2014. The intermediate effect of geographic proximity on intergenerational support. In: A Comparison of France and Bulgaria. Longitudinal and Life Course Research (CELLO) University of Antwerp, Research Centre for.
Hong, W., Su, Y.-S., 2013. The effect of institutional proximity in non-local university–industry collaborations: An analysis based on Chinese patent data. Research Policy 42 (2), 454–464.
Hughes, T., Webber, D., O'Regan, N., 2017. Achieving wider impact in business and management: analysing the case studies from REF 2014. Stud. High. Educ. 44 (4), 628–642.
Hung, S.W., Cheng, M.J., Hou, C.E., Chen, N.R., 2021. Inclusion in global virtual teams: exploring non-spatial proximity and knowledge sharing on innovation. J. Bus. Res. 128, 599–610.
Iacobucci, D., Perugini, F., 2023. Innovation performance in traditional industries: does proximity to universities matter? Technological Forecasting and Social Change 189. https://doi.org/10.1016/j.techfore.2023.122340.
Janssen, M.J., Abbasiharofteh, M., 2022. Boundary spanning R&D collaboration: key enabling technologies and missions as alleviators of proximity effects? Technological Forecasting and Social Change 180.
Johnston, A., Huggins, R., 2017. University-industry links and the determinants of their spatial scope: a study of the knowledge intensive business services sector. Pap. Reg. Sci. 96 (2), 247–260.
Johnston, A., Huggins, R., 2018. Partner selection and university-industry linkages: assessing small firms' initial perceptions of the credibility of their partners. Technovation 78, 15–26.
Kwon, H., Kim, J., Park, Y., 2017. Applying LSA text mining technique in envisioning social impacts of emerging technologies: the case of drone technology. Technovation 60-61, 15–28.
Lander, B., 2015. Proximity at a distance: the role of institutional and geographical proximities in Van'ouver's infection and immunity research collaborations. Ind. Innov. 22 (7), 575–596.
Lee, S., Bozeman, B., 2005. The impact of research collaboration on scientific productivity. Soc. Stud. Sci. 35 (5), 673.
Liang, X., Liu, A.M.M., 2018. The evolution of government sponsored collaboration network and its impact on innovation: a bibliometric analysis in the Chinese solar PV sector. Research Policy 47 (7), 1295–1308.
Mahdad, M., Minh, T.T., Bogers, M., Piccaluga, A., 2020. Joint university–industry laboratories through the lens of proximity dimensions: moving beyond geographical proximity. International Journal of Innovation Scie nce 12, 433–456.
Marchand, P., Ratinaud, P., 2012. L'analyse de similitude appliquée aux corpus te xtuels: les primaires socialistes pour l'élection présidentielle française (septembre-octobre 2011). *Actes 11eme Journ. Int. D'Analyse Stat.* Données Textuelles JAD T 2012, 687–699.
Marek, P., Titze, M., Fuhrmeister, C., Blum, U., 2017. R&D collaborations and the role of proximity. Regional Studies 51 (12), 1761–1773.
Marques, J., Caraça, J., Diz, H., 2006. How can university–industry–government interactions change the innovation scenario in Portugal?: the case of the University of Coimbra. Technovation 26 (4), 534–542.

Marrocu, E., Paci, R., Usai, S., 2013. Proximity, networking and knowledge production in Europe: what lessons for innovation policy? Technol. Forecast. Soc. Chang. 80 (8), 1484–1498.
Molas-Gallart, J., Tang, P., Morrow, S., 2000. Assessing the non-academic impact of grant-funded socio-economic research: results from a pilot study. Research Evaluation 9 (3), 171–182.
Moodysson, J., Coenen, L., Asheim, B., 2008. Explaining spatial patterns of innovation: analytical and synthetic modes of knowledge creation in the Medicon Valley life-science cluster. Environ Plan A 40 (5), 1040–1056.
Mora-Valentin, E.M., Montoro-Sanchez, A., Guerras-Martin, L.A., 2004. Determining factors in the success of R&D cooperative agreements between firms and research organizations. Research Policy 33, 17–40.
Muscio, A., Pozzali, A., 2013. The effects of cognitive distance in university-industry collaborations: some evidence from Italian universities. The Journal of Technology Transfer 38 (4), 486–508.
Nooteboom, B., 2000. Learning by interaction: absorptive capacity, cognitive distance and governance. J. Manag. Gov. 4 (1–2), 69–92.
Nooteboom, B., Vanhaverbeke, W., Duysters, G., Gilsing, V., van den Oord, A., 2007. Optimal cognitive distance and absorptive capacity. Research Policy 36 (7), 1016–1034.
Oliver, A.L., 2004. On the duality of competition and collaboration: network-based knowledge relations in the biotechnology industry. Scand. J. Manag. 20 (1–2), 151–171.
Ozcan, P., Eisenhardt, K.M., 2009. Origin of alliance portfolios: entrepreneurs, network strategies, and firm performance. Acad. Manage. J. 52 (2), 246–279.
Paier, M., Scherngell, T., 2011. Determinants of collaboration in European R&D networks: empirical evidence from a discrete choice model. Ind. Innov. 18 (1), 89–104.
Pavone, P., 2010. Sintagmazione del testo: una scelta per disambiguare la terminologia e ridurre le variabili di un'analisi del contenuto di un corpus, in: Bolasco, S., Chiari, Isabella, Giuliano, Luca (Eds.), Statistical Analysis of Textual Data. In: Proceedings °f 10th International Conference Journées d'Analyse Statistique des Données Textuelles 9–11 June–2010 - Sapienza University of Rome. Led on Line, Roma, pp. 131–140.
Pavone, P., 2018. Automatic multiword identification in a specialist corpus. In: In *Tracing the Life Cycle of Ideas in the Humanities and Social Sciences*, Ed. Springer, Cham, A. Tuzzi.
Perkmann, M., Walsh, K., 2007. University–industry relationships and open innovation: towards a research agenda. Int. J. Manag. Rev. 9, 259–280.
Pinto, H., Fernández-Esquinas, M., Uyarra, E., 2013. Universities and knowledge-intensive business services as sources of knowledge for innovative firms in peripheral regions. Reg. Stud. 49 (11), 1–19.
Ponds, R., Van Oort, F., Frenken, K., 2007. The geographical and institutional proximity of scientific collaboration networks. Papers in Regional Science 86 (3), 423–443.
Ponds, R., Van Oort, F., Frenken, K., 2010. Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. Journal of Economic Geography 10 (2), 231–255.
Popping, R., 1999. Computer-assisted text analysis. Computer-Assisted Text Analysis 1–240.
Qiu, H., Chreim, S., Freel, M. 2023. A tension lens for understanding entrepreneurship-related activities in the university. *Technological Forecasting and Social Change* 186.
Rau, H., Goggins, G., Fahy, F., 2018. From invisibility to impact: Recognising the scientific and societal relevance of interdisciplinary sustainability research. Research Policy 47 (1), 266–276.
Reale, E., et al., 2017. A review of literature on evaluating the scientific, social and political impact of social sciences and humanities research. Research Evaluation 27 (4), 298–308.
Rocancio Marin, J., 2022. How do entrepreneurial universities integrate society for impactful technology transfer and entrepreneurship? DRUID Society.
Rodan, S., Galunic, C., 2004. More than network structure: how knowledge heterogeneity influences managerial performance and innovativeness. Strateg. Manag. J. 25, 541–562.
Rosli, A., De Silva, M., Rossi, F., Yip, N., 2018. The long-term impact of engaged scholarship: how do SMEs capitalise on their engagement with academics to explore new opportunities? Int. Small Bus. J. 36 (4), 400–428.
Rossi, F., Rosli, A., 2015. Indicators of university-industry knowledge transfer performance and their implications for universities: evidence from the United Kingdom. Stud. High. Educ. 40 (10), 1970–1991.
Rossi, F., Rosli, A., Yip, N., 2017. Academic engagement as knowledge co-production and implications for impact. J. Bus. Res. 80, 1–9.
Rossi, F., De Silva, M., Baines, N., Rosli, A., 2022. Long-term innovation outcomes of university–industry collaborations: the role of 'bridging' vs 'blurring' boundary-spanning practices. British Journal of Management 33 (1), 478–501.
Rynes, S.L., Bartunek, J.M., Daft, R.L., 2001. Across the great divide: knowledge creation and transfer between practitioners and academics. Acad. Manage. J. 44 (2), 340–355.
Saldaña, J., 2013. The Coding Manual for Qualitative Researchers. Sage Publications, Second. Edition.
Salter, A.J., Martin, B.R., 2001. The economic benefits of publicly funded basic research: a critical review. Res. Policy 30, 509–532.
Salton, G., 1989. Automatic Text Processing: The Transformation, Analysis and Retrieval of Information by Computer. Addison-Wesley.
Salton, G., Buckley, C., 1988. Term weighting approches in automatic text retrieval. Commun. ACM 26 (11), 1022–1036.
Salton, G., Yu, C.T., 1975. A theory of term importance in automatic text analysis. Journal of the ASIS 26 (1), 33–44.
Santamaria, L., Nieto, M.J., Rodriguez, A. 2021. Failed and successful innovations: The role of geographic proximity and international diversity of partners in technological collaboration. *Technological Forecasting and Social Change* 166, doi:https://doi.org/10.1016/j.techfore.2021.120575.
Siebdrat, F., Hoegl, M., Ernst, H., 2014. Subjective distance and team collaboration in distributed teams. J. Prod. Innov. Manag. 31 (4), 765–779.
Siegel, D.S., Leih, S., 2018. Strategic management theory and universities: An overview of the special issue. Strateg. Organ. 16 (1), 6–11.
Siemieniako, D., Kubacki, K., Mitręga, M., 2021. Inter-organisational relationships for social impact: a systematic literature review. J. Bus. Res. 132 (2), 453–469.
Smolinski, A., Bondaruk, J., Pichlak, M., Trzaski, L., Uszok, E., 2015. Science-economy-technology concordance matrix for development and implementation of regional smart specializations in the Silesian Voivodeship. Poland. Scientific World Journal 126760.
Steinmo, M., Lauvås, T., 2022. The Role of Proximity Dimensions in University-Industry Collaboration: A Review and Research Agenda (Handbook of Proximity Relations).
Stock, G., Tatikonda, M., 2000. A typology of project-level technology transfer processes. J. Oper. Manag. 18 (6), 719–737.
Storper, M., Venables, A.J., 2004. Buzz: face-to-face contact and the urban economy. Journal of Economic Geography 4 (4), 351–370.
Sullivan, D., 2001. Document Warehousing and Text Mining. Wiley, New York.
Sun, Y., Cao, C., 2015. Intra- and inter-regional research collaboration across organizational boundaries: evolving patterns in China. Technological Forecasting and Social Change 96, 215–231.
Taheri, M., van Geenhuizen, M., 2016. Teams' boundary-spanning capacity at university: performance of technology projects in commercialization. Technological Forecasting and Social Change 111, 31–43.
Ternouth, P., Garner, C., Wood, L., Forbes, P., 2012. Key Attributes for Successful Knowledge Transfer Partnerships. Council for Industry and Higher Education, London.
Thomas, L., Ambrosini, V., 2021. The future role of the business school: a value Cocreation perspective. Acad. Manag. Learn. Edu. 20 (2), 249–269.
Van Looy, B., Debackere, K., Andries, P., 2003. Policies to stimulate regional innovation capabilities via university-industry collaboration: an analysis and an assessment. R&D Manag. 33 (2), 209–229.
Villani, E., Rasmussen, E., Grimaldi, R., 2017. How intermediary organizations facilitate university–industry technology transfer: a proximity approach. Technological Forecasting and Social Change 114, 86–102.
Vlaisavljevic, V., Cabello-Medina, C., Pérez-Luño, A., 2016. Coping with diversity in alliances for innovation: the role of relational social capital and knowledge codifiability. British Journal of Management 27 (2), 304–322.
Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press.
Weiss, S.M., 2010. Text Mining: Predictive Methods for Analyzing Unstructured Information. Springer, New York.
Wirsich, A., Kock, A., Strumann, C., Schultz, C., 2016. Effects of university–industry collaboration on technological newness of firms. Journal of Product Innovation Management 33 (6), 708–725.
Woltmann, S., Alkaersig, L., 2017. Tracing Knowledge Transfer from University to Industry: A Text Mining Approach, *Proceedings of the Academy of Management Conference* 2017.
Woltmann, S.L., Alkaersig, L., 2018. Tracing university-industry knowledge transfer through a text-mining approach. Scientometrics 117 (1), 449–472.
Wuchty, S., Jones, B.F., Uzzi, B., 2007. The increasing dominance of teams in production of knowledge. Science 316 (5827), 1036–1039.
Wynn, M., Turner, P., 2013. Effecting successful knowledge transfer: lessons from the UK knowledge transfer partnership scheme. International Journal in Education 7 (3), 293–312.
Xu, S., Hao, L., Yang, G., Lu, K., An, X., 2021. A topic models based framework for detecting and forecasting emerging technologies. *Technological Forecasting and Social Change* 162.
Yli-Renko, H., Autio, E., Sapienza, H.J., 2001. Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. Strateg. Manag. J. 22 (6–7), 587–613.

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