EXPLORING THE NATURE OF BENEFITS AND COSTS OF OPEN INNOVATION FOR UNIVERSITIES BY USING A STOCHASTIC MULTI-CRITERIA CLUSTERING APPROACH: THE CASE OF UNIVERSITY-INDUSTRY RESEARCH COLLABORATION

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Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the
Master of Science in Management

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Dedication

In dedication to my lovely wife, Zahra, who inspires me to live life to the fullest in each moment.

Acknowledgment

I would like to thank the following people who have helped me undertake this research:

My supervisor, professor Sarah Ben Amor, for her enthusiasm for the project, for her support, encouragement, and patience;

For their contributions to research review, research question, and data collection:

Professor Wadid Lamine,

Professor Sandra Schillo.

Abstract

Open innovation that Henry Chesbrough introduced in 2003 promotes the usage of the input of outsiders to strengthen internal innovation processes and the search for outside commercialization opportunities for what is developed internally. Open innovation has enabled both academics and practitioners to design innovation strategies based on the reality of our connected world.

Although the literature has identified and explored a variety of benefits and costs, to the best of our knowledge, no study has reviewed the benefits and costs of open innovation in terms of their importance for strategic performance. To conduct such a study, we need to take into account two main issues. First, the number of benefits and costs of open innovation are multifold; so, to have a comprehensive comparison, a large number of benefits and costs must be compared. Second, to have a fair comparison, benefits and costs must be compared in terms of different performance criteria, including financial and non-financial.

Concerning the issues above, we will face a complex process of exploring benefits and costs. In this regard, we use multiple criterion decision-making (MCDM) methods that have shown promising solutions to complex exploratory problems. In particular, we present how using a stochastic multi-criteria clustering algorithm that is one of the recently introduced MCDM methods can bring promising results when it comes to exploring the strategic importance of benefits and costs of open innovation.

Since there is no comprehensive understanding of the nature of the benefits and costs of open innovation, the proposed model aims to cluster them into hierarchical groups to help researchers identify the most crucial benefits and costs concerning different dimensions of performance. In addition, the model is able to deal with uncertainties related to technical parameters such as criteria weights and preference thresholds. We apply the model in the context of open innovation for universities concerning their research collaboration with industries. An online survey was conducted to collect experts' opinions on the open-innovation benefits and costs of university-industry research collaboration, given different performance dimensions.

The results obtained through the cluster analysis specify that university researchers collaborate with industry mainly because of knowledge-related and research-related reasons rather than economic reasons. This research also indicates that the most important benefits of university-industry research collaboration for universities are implementing the learnings, increased know-how, accessing specialized infrastructures, accessing a greater idea and knowledge base, sensing and seizing new technological trends, and keeping the employees engaged. In addition, the results show that the most important costs are the lack of necessary resources to monitor activities between university and industry, an increased resistance to change among employees, conflict of interest (different missions), an increased employees' tendency to avoid using the knowledge that they do not create themselves, paying time costs associated with bureaucracy rules, and loss of focus. The research's findings enable researchers to analyze open innovation's related issues for universities more effectively and define their research projects on these issues in line with the priorities of universities.

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1. Introduction

Innovation is proven as a critical economic driver in the economy (Hidalgo & Albors, 2008). Organizations must continuously innovate to meet changing customer demands and expectations and to benefit from new opportunities. Decades ago, Schumpeter and Capitalism (1942) hypothesized that organizations need innovation to renovate the value of their asset endowment. Even before this, innovation was perceived as necessary in facing economic changes (Lorenzi, 1912; Veblen, 1899).

Historically, different theoretical views on innovation have been developed. As one of the recent views on innovation, open innovation paints a much more comprehensive picture and defines innovation as a series of stages permeable to knowledge and technologies (Fleming & Waguespack, 2007). In innovation management, open innovation has become one of the topical issues attracting increasing scholarly attention (e.g., (Dahlander & Gann, 2010) and (Randhawa et al., 2016)). Henry Chesbrough, who coined the term "Open Innovation" in 2003, describes open innovation as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Henry, 2003). Chesbrough and Bogers (2014) later redefined open innovation as "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries."

In closed innovation, as the old innovation model, new ideas and technologies are explored and delivered by internal expertise and resources (Panduwawala et al., 2009). As figure 1 shows, in closed innovation, the firm's boundaries are rigid and do not let knowledge through, leading to a lack of information sharing between different parties. In reality, creative ideas sequentially flow to the research stage and then to the development stage, while some ideas may be filtered during the research process (Chesbrough, 2003).

On the other hand, open innovation promotes the usage of the input of outsiders to strengthen internal innovation processes and the search for outside commercialization opportunities for what is developed internally (H. Chesbrough, 2006). Open innovation has enabled both academics and practitioners to design innovation strategies based on the reality of our connected world.

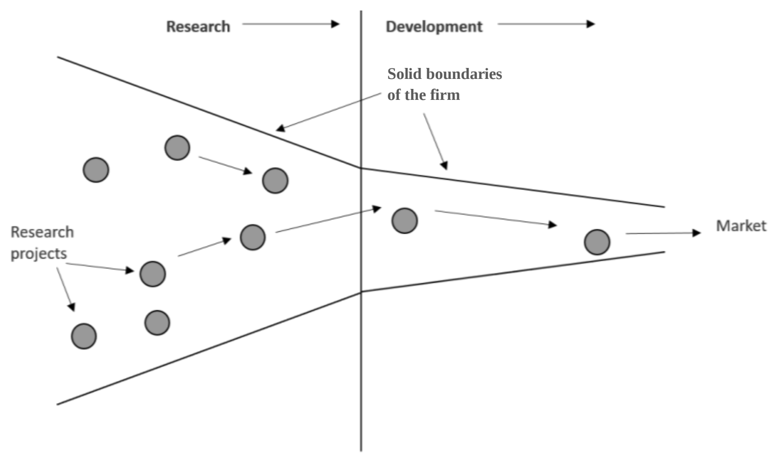

Figure 1.a The closed innovation funnel - Depicted based on Chesbrough's (2003) article

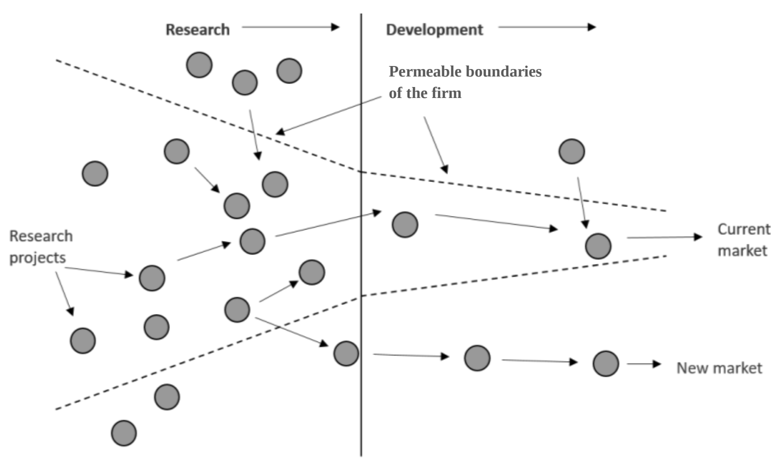

Figure 1.b The open innovation funnel - Depicted based on Chesbrough's (2003) article

Practicing open innovation has many benefits, including increased revenue (D’Este & Patel, 2007), increased know-how (Han, 2017), improved brand reputation (Chesbrough et al., 2014), reduced R&D Costs (Greco et al., 2019), improved long-term profitability (Caputo et al., 2016), etc. On the other hand, it is also associated with different costs, including the reduced rarity of knowledge assets (Torkkeli et al., 2009), increased possibility of knowledge leakage (Salge et al., 2013), loss of focus Helm et al. (2019), lack of the necessary resources to monitor activities (Manzini et al., 2017), etc.

Since the incarnation of the open innovation concept, early in the 21st century, the concept has evolved and matured noticeably. However, the literature still suffers from insufficient scientific evidence regarding the benefits and costs of open innovation strategies (West, 2020). Although some studies (e.g., (Noh, 2015), (Greco et al., 2019), and (Caputo et al., 2016)) in the literature have identified and explored a variety of benefits and costs of open innovation and also of university-industry research collaboration in terms of their importance to firm performance, they suffer from a significant shortcoming. Performance is a multi-dimensional concept (Kennerley & Neely, 2002) and must be evaluated from different dimensions, including financial, customer, business processes, and learning and growth (Kaplan & Norton, 2005). To our best knowledge, none of the studies in the literature allows scholars to compare the benefits and costs of university-industry research collaboration in terms of different dimensions of performance.

In response to the discussed shortcoming, we explore the benefits and costs of open innovation and particularly of university-industry collaboration in view of different dimensions of performance. In this regard, we use multiple criterion decision-making (MCDM) methods that have shown promising solutions to the complex exploratory problem (Kumar et al., 2017; Mardani et al., 2015). In particular, we present how using a stochastic multi-criteria clustering algorithm that is one of the recently introduced MCDM methods can bring promising results when it comes to exploring the nature of the benefits and costs of open innovation.

Since open innovation is a context-dependent issue (Schroll & Mild, 2012), we need to explore the benefits and costs of open innovation in a specific context. On the other hand, there has been an increasing interest among open innovation scholars in the context of university-industry research collaboration (Cesaroni & Piccaluga, 2016; Perkmann & Walsh, 2007). In this regard, we explore the benefits and costs of open innovation for universities in the context of university-industry research collaboration.

We contribute to work in this area by clustering the benefits and costs of university-industry research collaboration and discussing clusters' nature. The findings of this research allow careful consideration of a trade-off between benefits and costs of open innovation, particularly in the context of university-industry research collaboration.

The remainder of the thesis proposal is organized as follows: Section 2 reviews the studies that explored open innovation in terms of its benefits and costs. In addition, it particularly reviews the literature on the benefits and costs of university-industry research collaboration. Section 3 proposes the research question based on the research gap, and section 4 presents the research methodology. The research application and timeline are expressed in sections 5 and 6, respectively.

2. Literature review

For this study, we searched the Scopus[1] database using the combination of the search terms "open innovation", "university industry", "advantage", "benefit", "bright side", "pro", "output", "outcome", "impact", "performance measure", "positive", "asset", "strength", "gain", "opportunity", "cost", "disadvantage", "risk", "dark side", "con", "negative", "drawback", "liability", "weakness", and "loss". Limiting the language to English and the study types to "article", "book", and "book chapter", we found more than 2300 studies[2] on the topic of benefits and costs of open innovation and more than 1100 studies[3] on the topic of benefits and costs of university-industry research collaboration. Reading the documents' abstracts, we retrieved more than 200 studies to be reviewed for this study. We did not apply any date limit and assessed the studies based on their relevance to the research objectives.

[1] The world's largest searchable citation and abstract source of searching literature (Schotten et al., 2017)

[2] The search string: TITLE-ABS-KEY ("open innovation" AND ("advantage" OR "benefit" OR "bright side" OR "pro" OR "output" OR "outcome" OR "impact" OR "performance measure" OR "positive" OR "asset" OR "strength" OR "gain" OR "opportunity" OR "advantages" OR "benefits" OR "bright sides" OR "pros" OR "outputs" OR "outcomes" OR "impacts" OR "performance measures" OR "positives" OR "assets" OR "strengths" OR "gains" OR "opportunities")) OR TITLE-ABS-KEY ("open innovation" AND ("cost" OR "disadvantage" OR "risk" OR "dark side" OR "con" OR "negative" OR "drawback" OR "liability" OR "weakness" OR "loss" OR "costs" OR "disadvantages" OR "risks" OR "dark sides" OR "cons" OR “negatives” OR “drawbacks” OR “liabilities” OR “weaknesses” OR “losses”))

[3] The search string: TITLE-ABS-KEY ("university industry" AND ("advantage" OR "benefit" OR "bright side" OR "pro" OR "output" OR "outcome" OR "impact" OR "performance measure" OR "positive" OR "asset" OR "strength" OR "gain" OR "opportunity" OR "advantages" OR "benefits" OR "bright sides" OR "pros" OR "outputs" OR "outcomes" OR "impacts" OR "performance measures" OR "positives" OR "assets" OR "strengths" OR "gains" OR "opportunities")) OR TITLE-ABS-KEY ("university industry " AND ("cost" OR "disadvantage" OR "risk" OR "dark side" OR "con" OR "negative" OR "drawback" OR "liability" OR "weakness" OR "oss" OR "costs" OR "disadvantages" OR "risks" OR "dark sides" OR "cons" OR "negatives" OR "drawbacks" OR "liabilities" OR "weaknesses" OR "losses"))

In addition, we use backward and forward snowballing[4] in order to find pertinent studies. We found more than 100 pertinent studies through backward and forward snowballing. Figure 2 shows the sources and ways that we used to find and assess pertinent scientific studies.

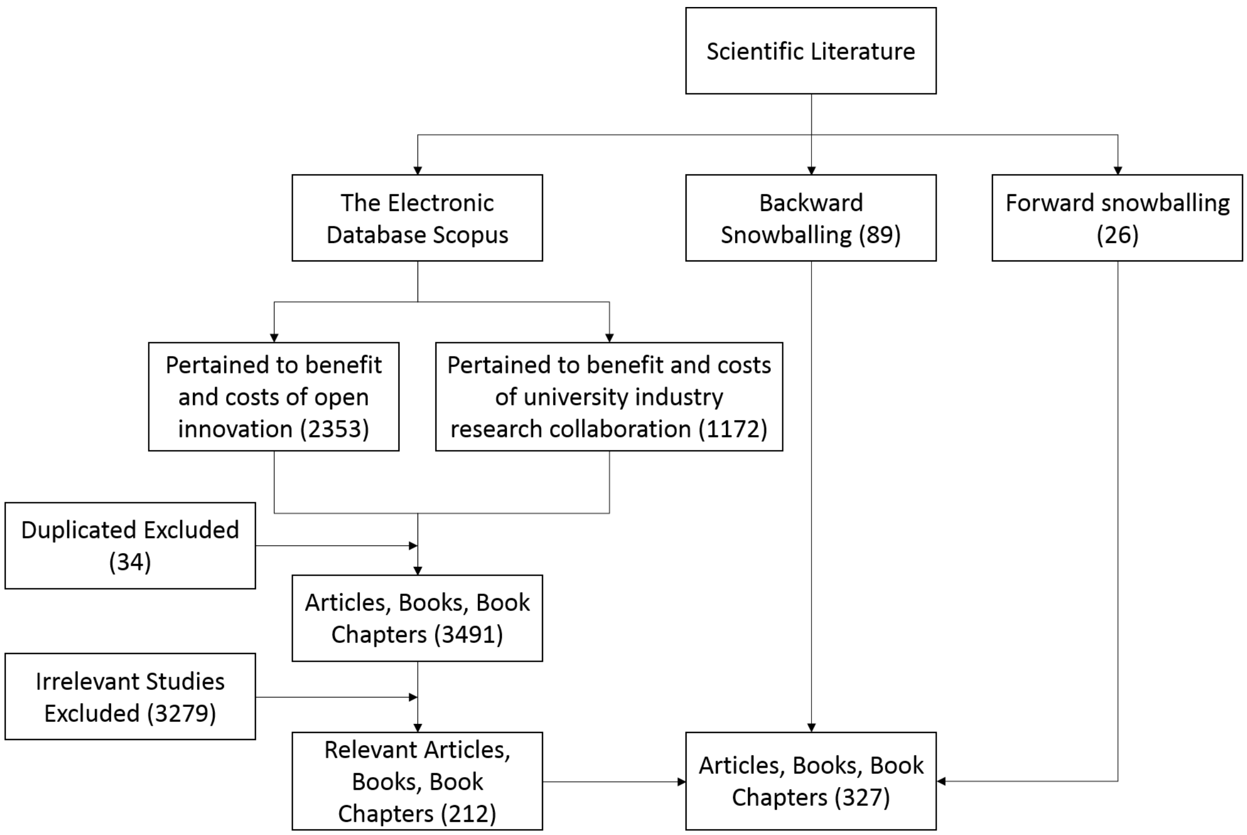

Figure 2 the sources and ways that have been used to find and assess scientific studies

2.1. Definition of research collaboration

The term "research collaboration" is generally understood to indicate scientific research (Amabile et al., 2001; Katz & Martin, 1997). Tett et al. (2003) state that collaborative scientific research is

[4] Using the references and the citations is referred to as backward and forward snowballing respectively (Jalali & Wohlin, 2012).

a dynamic research activity that normally deals with complex questions and engages both academics and practitioners specialized in their fields. Mwapwele and van Biljon (2021) clarify that collaborative scientific research can potentially lead to publications but does not necessarily have to.

The literature on research collaboration includes a broad spectrum of definitions of what research collaboration constitutes. For instance, Rhoten and Pfirman (2007) describe research collaboration as the "collaborat[ion] in teams or networks that seek to exchange and/or create new tools, concepts data, methods, or results." While, other authors like Fox and Mohapatra (2007) define the phenomenon as the "cooperation of scientists with students, technicians, and others of both equal and unequal rank". This variety of definitions for the term "research collaboration" and the lack of a universally accepted definition can create ambiguity (Mwapwele & van Biljon, 2021; Smykla & Zippel, 2010).

In this study, to remove ambiguity from the interpretation of the term "research collaboration", we indicate research collaboration as below: "The collaboration between two or more parties (in the context of university-industry research collaboration: at least one university and one private, public or global enterprise) pursuing mutually interesting and beneficial research that potentially can lead to publications, but do not necessarily have to."

2.2. Benefits and costs of open innovation

Practicing open innovation has many benefits, including increased revenue (D'Este & Patel, 2007), increased know-how (Han, 2017), improved brand reputation (Chesbrough et al., 2014), reduced R&D Costs (Greco et al., 2019), improved long-term profitability (Caputo et al., 2016), etc. On the other hand, it is also associated with different costs, including the reduced rarity of knowledge assets (Torkkeli et al., 2009), increased possibility of knowledge leakage (Salge et al., 2013), loss of focus Helm et al. (2019), lack of the necessary resources to monitor activities (Manzini et al., 2017), etc. In the following, we present a wide range of the benefits and costs of open innovation that have been addressed in the literature.

Benefits of open innovation

Previous studies have identified and explored various benefits for firms using open innovation activities (Chesbrough et al., 2018; Miglietta et al., 2017). Many scholars maintain that open innovation significantly improves innovation performance (Greco et al., 2015) and firm performance by building on strong ties with innovation network partners, co-innovation, and co-development (Bengtsson et al., 2015; Caputo et al., 2016; Chesbrough, 2003). Cheng and Huizingh (2014) maintain that performing open innovation activities can foster all four dimensions of innovation performance: new product (or service) innovativeness, new product (or service) success, customer performance, and financial performance.

Using open innovation has its respective benefits, which can be pecuniary and non-pecuniary, tactical or strategic, short-term or long-term (Dahlander & Gann, 2010; Huizingh, 2011). Chesbrough et al. (2018) consider four types of rewards for firms that implement open innovation activities: prosocial rewards (e.g., a sense of belonging to something important), intrinsic rewards (e.g., enjoyment of intellectual challenges), extrinsic nonpecuniary rewards (e.g., learning, and faster diffusion of ideas), and extrinsic pecuniary rewards (e.g., monetary awards).

The financial benefits of open innovation can include decreased costs, improved long-term profitability, and decreased investment costs (Caputo et al., 2016; Noh, 2015). It also includes shared R&D costs and reduced financial risks (Gillespie et al., 2019). In addition, open innovation helps firms achieve strategic advantages through external technology exploitation or commercialization (Helm et al., 2019). In other words, open innovation can be viewed as a catalyst for production and sales. Panagopoulos and Park (2018) maintain that open innovation can enhance future bargaining positions and justify some R&D activities that cannot be justified without counting on the potential of new players.

Other benefits of open innovation include reduced time to market (Huston & Sakkab, 2006; Sarkar & Costa, 2008), increased market efficiency (Szutowski, 2018), and reduced risk of product failure (Ferraris et al., 2017; Sarkar & Costa, 2008). Moreover, Vanhaverbeke et al. (2008) emphasize that open innovation enables firms to access a wide range of externally developed inventions just by acquiring minority stakes in high-tech start-ups and investing in venture capital funds. Also, they maintain innovative firms can benefit from the delayed financial commitment and even choose either the strategies of expediting or delaying an exit. In addition, Van Geenhuizen and Soetanto (2013) state that open innovation may help universities reduce market risks by learning through relationships with other firms and customers.

Furthermore, open innovation increases employee engagement (Hosseini et al., 2017) and helps firms transfer their norms toward collaboration (Leckel et al., 2020; Suh & Kim, 2012). Open innovation also opens doors for firms to access talents (Del Giudice et al., 2018). It can give firms a particular brand reputation and helps to gain consumers' trust in their brand (Chesbrough et al., 2014). Open innovation also can help firms increase their agility (Cepeda & Arias-Pérez, 2019), improve their ability to sense and seize new technological trends (Grimaldi et al., 2013), build a strong commercial community (Wyckoff & Koreen, 2010), and increase the number of their patents (Lichtenthaler, 2010; Ren & Su, 2015). Gassmann and Enkel (2004) also stress that open innovation brings commercial benefits through licensing or selling patents.

Reed et al. (2012) conclude that open innovation allows firms to rent from organizational cultures, innovation management systems, and the reputations of other parties. Moreover, open innovation increases resource availability of the organization, stimulates innovation creation, and improves strategic thinking and team working (Rogo et al., 2014). Stroh (2019) states open innovation brings a diversity of paradigms of thought, ideas, and problem-solving methods.

Almirall and Casadesus-Masanell (2010) present several benefits of open innovation, including improved user adoption, enhanced network effects, a created sense of urgency to act on ideas or technology, and a developed culture that fosters innovation. Bengtsson et al. (2015) maintain although open innovation increases the number of innovations, it also has a positive impact on the radicalness of innovations - the degree to which innovations are disruptive and cause fundamental changes in the internal processes or outputs of organizations (Damanpour & Aravind, 2012)

Rocha et al. (2019) conclude that open innovation changes the nature of the organizational structure and decentralizes the decision-making process leading to added value to the products and services. In addition, open innovation reduces individualistic behavior (Breunig et al., 2014), improves organizational learning capacity (Ovuakporie et al., 2021), and also triggers a positive reaction by stockholders (Noh, 2015).

Costs of open innovation

Beside the benefits of open innovation, there are different costs associated with it. Hewitt-Dundas and Roper (2018) demonstrate through an empirical qualitative study that limited information on functional capabilities and limited information on trustworthiness are the leading causes of open innovation market failures. Limited information on functional capabilities refers to imperfect and asymmetric information about potential partners' functional abilities. It may cause a failure to find suitable partners or lead to forming open innovation relationships with the wrong partners. In this case, the wrong partners' selection negatively affects outputs (Kivistö, 2005). Limited information on trustworthiness talks about firms' incomplete information on the reliability and integrity of open innovation partners (Squire et al., 2009). Limited information on trustworthiness can reduce the efficacy of open innovation (Jiang et al., 2011).

Martovoy et al. (2015) disclose that by using open innovation, firms need to deal with two issues, including bureaucracy rules and time costs associated with cooperation. Fu et al. (2019) emphasize that open innovation requires firms to pay more costs because of cooperation with external entities; they also stress that firms need to pay extra costs for relationship maintenance.

Torkkeli et al. (2009) stress that open innovation can adversely affect firms' rarity of knowledge and competitive advantage. Many scholars also conclude a high level of openness could hurt the production of new knowledge and, subsequently, the firm performance (e.g., (Cruz-González et al., 2015; Veer et al., 2016)). One of the significant risks of implementing open innovation practices is knowledge leakage which can bring irreparable damage to open innovation practitioners (Alberti & Pizzurno, 2017). Based on many case studies of knowledge leakage in joint research and development (R&D) projects in large firms in Sweden, Frishammar et al. (2015) infer that not only core knowledge must be protected from leakage, but also non-core knowledge must be protected since its leakage can have even more severe destructive effects. Dahlander and Gann (2010) also emphasized that firms using open innovation approach must bear the risk of disclosure of core technology.

Hannen et al. (2019) and de Araújo Burcharth et al. (2014) maintain that the not-invented-here (NIH) syndrome, which is defined by a tendency for people and organizations to avoid using or buying products, research, standards, or knowledge they did not create themselves, plays a crucial role in the failure of open innovation. Moreover, Mortara et al. (2010) stress while openness causes cultural changes, employees' resistance to change must be considered a pivotal challenge.

Furthermore, open innovation may lead to the loss of focus and make the firms lose their core businesses since they direct the firm's attention toward technologies that are not necessarily usable for the core business (Helm et al., 2019). Besides, Almirall and Casadesus-Masanell (2010) reveal that by using open innovation, firms need to consider the cost of losing control of the product's technological trajectory. Yoon et al. (2016) also emphasize the more firms use open innovation practices, the more it becomes difficult to retain exclusive possession of the achievements.

2.3. Benefits and costs of university-industry research collaboration

The university-industry collaboration had received increased attention since the late 1970s (Caloghirou et al., 2001), more than two decades before the time Chesbrough coined the term "open innovation." However, after the incarnation of the open innovation concept, university-industry collaboration became recognized as a promising mechanism to promote open innovation (El-Ferik & Al-Naser, 2021), and since then, there has been an increasing interest in the role of universities in knowledge transfer through open innovation (Cesaroni & Piccaluga, 2016; Di Nauta et al., 2018; Gulbrandsen & Slipersaeter, 2007), particularly when it comes to university-industry research collaboration (Perkmann & Walsh, 2007; Striukova & Rayna, 2015). In the following, we present a wide range of benefits and costs of university-industry research collaboration that have been addressed in the literature.

Benefits of university-industry research collaboration

The university-industry research collaboration provides university researchers a valuable opportunity to get exposure to the industry. Lee and Bozeman (2005) conclude that university researchers collaborating with industry are more productive in terms of publication than researchers working alone. Moreover, Lee and Win (2004) maintain that university-industry research collaboration helps researchers direct their research toward real market needs and design their research programs to meet industry expectations. Barnes et al. (2002) also hypothesize that university researchers keep up with technological development and contribute to the local economy through collaboration with industry. Ankrah and Al-Tabbaa (2015) emphasize that university-industry research collaboration may result in new business opportunities, economic growth, and wealth creation.

Jonsson et al. (2015) declare that university-industry collaboration promotes academic engagement. D’Este and Patel (2007) maintain university-industry research collaboration results in new revenue streams. D'este and Perkmann (2011) argue that scholars who interact with industry can build the capabilities necessary to bridge the gap between science and application. They also discuss how university-industry research collaboration positively contributes to having access to technological infrastructures. D’este and Perkmann (2011) stress that interactions with industries enable universities to have access to valuable data, and Guerrero et al. (2016) also conclude that it can significantly support the entrepreneurial role of universities.

Pittaway and Cope (2007) state that university researchers' engagement with industry encourages them to work outside their comfort zone. Lee (2000) maintains that university-industry research collaboration helps academics gather information for teaching, including feedback from experts in the industry and information on industry problems. In addition, collaborating with industry makes researchers capable of making sense of other people and improves their "integrating" capability (Arbussà & Coenders, 2007); It also helps them build more professional ties and accelerate their professional developments (Ahn et al., 2016).

Caloghirou et al. (2001) conclude that the primary benefits of university-industry research collaboration include sharing R&D costs, building research synergies, and keeping up with major technological developments. Also, Fransman and Tanaka (1995) present that university-industry research collaboration results in risk-sharing, creates new investment options, and reduces uncertainties related to research projects.

Furthermore, universities can secure money to fund their projects through collaboration with industry (Colombo et al., 2021). The university-industry collaboration also enables university researchers to increase their know-how (Arvanitis et al., 2008) and solve technical problems (Van der Sijde, 2012). It also increases the capacity of universities to attract new students, elevates their prestige, and supports their postdocs (Lacy et al., 2014). Universities can access equipped industrial research sites (Malfroy, 2011), gain managerial experience, and formulate new hypotheses (Valentín, 2000) through collaboration with industry. Besides, university-industry research collaboration is associated with a higher patenting rate (Marullo et al., 2021).

Costs of university-industry research collaboration

By considering the other side of the coin, Håkansson and Waluszewski (2007) maintain that the costs associated with university-industry research collaboration arise because of differences in the ecosystems. Bruneel et al. (2010) conclude that universities and industries have different priorities that make their collaboration problematic and less effective. Also, Almeida et al. (2011) and Colombo et al. (2021) explain universities need to pay the costs of bridging the differences between the university and industry when it comes to research collaboration. They explain that the differences can be occurred due to diffident cultures, habits, norms, values, rules, practices, incentives, and languages.

Stephan (1996) explains that university researchers have a strong desire to disseminate their knowledge as their career success is linked to publishing their research; On the contrary, entrepreneurial ventures are inclined to use exclusive knowledge to gain a competitive advantage. Accordingly, entrepreneurial ventures try to protect their knowledge through intellectual property rights, whereas university researchers desire to publish collaborative research achievements (Oxley, 1997). In this regard, collaboration with industry may limit or cause delays in the publication of scientific articles (Blumenthal et al., 1996; Campbell et al., 2000).

As another cost for university-industry research collaboration, Faems et al. (2010) refer to the increased cost due to coordination and synchronization of open innovation practices. Leydesdorff and Ivanova (2016) stress that open innovation can waste energy and time since there would be an overlap between the activities that the university and industry must handle. Moreover, university-industry research collaboration is time-expensive for all the people involved because it can be logistically complex and require universities to spend time scouting potential partners (Locatelli et al., 2021).

From a knowledge management perspective, Lacy et al. (2014) maintain that a high amount of expertise and scientific resources between university and industry can lead to undesirable knowledge redundancy. Also, Salge et al. (2013) state that using open innovation approach can make universities vulnerable to knowledge leakage and imitation. In addition, Kathoefer and Leker

(2012) maintain that NIH syndrome adversely affects open innovation in the academic context, like the industrial context.

3. Research question and major contribution

Academics and practitioners need to deepen their knowledge about both benefits and costs of open innovation to have a comprehensive outlook on this developing phenomenon in innovation. It helps them make informed and robust decisions in facing many uncertainties about open innovation (Greco et al., 2019; Ullrich & Vladova, 2016). Still, despite the importance of the issue, exploring the costs of open innovation along with its benefits has been paid very little attention in the literature (Greco et al., 2019; Laursen & Salter, 2014; Monteiro et al., 2017; West & Bogers, 2017).

A few studies in the literature on open innovation and also university-industry research collaboration have explored the benefits and costs of open innovation in terms of their importance to firm performance. For instance, Noh (2015) and Greco et al.'s (2019) explore the benefits and costs of open innovation in terms of their importance to financial and innovation performances, respectively. Caputo et al. (2016) investigate the benefits and costs of open innovation in terms of their importance to both financial and innovation performances, and Soh and Subramanian (2014) evaluate the benefits and costs of university-industry research collaboration in terms of their importance to patent performances.

Although some studies in the literature have identified and explored a variety of benefits and costs of open innovation and also of university-industry research collaboration in terms of their importance to firm performance, they suffer from a significant shortcoming. Performance is a multi-dimensional concept (Kennerley & Neely, 2002) and must be evaluated from different dimensions, including financial, customer, business processes, and learning and growth (Kaplan & Norton, 2005). To our best knowledge, none of the studies in the literature allows scholars to compare the benefits and costs of university-industry research collaboration in terms of different dimensions of performance.

In response to the discussed shortcoming, we want to explore a considerable amount of benefits and costs referred to in the literature - which are above thirty items - in view of different aspects of performance. In this case, we use a multi-criteria decision-making (MCDM) method (Triantaphyllou, 2000) in which benefits and costs are alternatives, and the different aspects of performance are criteria. In the following, we discuss why the multi-criteria decision-making (MCDM) approach can bring promising results when it comes to exploring the nature of the benefits and costs of open innovation.

To facilitate the decision-making process, scholars have introduced different methods such as consensus (Humphrey-Murto et al., 2017), knowledge-driven (Zhang et al., 2017), simulation-based (Völkner & Werners, 2002), multi-criteria (Triantaphyllou, 2000), statistical (Raiffa & Schlaifer, 1961), game theory-based (Kelly, 2003) and machine learning-based (Ziora, 2020) decision-making methods. For exploring the nature of benefits and costs of open innovation., the Multi-Criteria Decision Making methods can provide significant benefits compared to many other methods.

First, MCDM methods provide a compromise solution; however, they let decision-makers have their particular solutions (Guitouni & Martel, 1998). This point is important since we need to provide a compromise solution out of various conflicting views provided by different experts. Second, MCDA methods are broadly considered helpful in solving decision-making problems when multiple conflicting criteria are involved and need to be evaluated (Javanbarg et al., 2012). This feature is important in our case; since four different criteria must be taken into account to explore the benefits and costs of open innovation. Third, using MCDM methods allows researchers to compare a wide range of alternatives/variables (Guitouni & Martel, 1998); however, common analytical methods such as regression are not potent enough to analyze a wide range of alternatives/variables because of endogeneity issues (Veblen, 1899).

Fourth, MCDM methods mainly benefit from both quantitative and qualitative methods (Bhole & Deshmukh, 2018), while many other methods rely just on qualitative evaluation (e.g., consensus decision-making (Humphrey-Murto et al., 2017)) or just on quantitative evaluation (e.g., machine learning-based decision-making (Ziora, 2020)). In this regard, we can gather subjective information provided by different experts relying on qualitative aspects of the MCDM methods and then use complex quantitative methods to analyze our data to find an ingenious and compromise solution. Lastly, because of the particular characteristics of MCDM methods, such as their potential to analyze qualitative and experts' opinions, they are effective not only for decision-making problems but also for exploratory investigation. (Kabak & Dağdeviren, 2014; Lu et al., 2013). This point is important since this research is an exploratory study.

All included, using an MCDM approach, we will analyze the benefits and costs of open innovation for universities concerning their research collaboration with industries. In particular, we will find an answer to the question of "What are the main benefits and costs of open innovation for universities in terms of their effects on strategic performance aspects - in the case of university-industry research collaboration?"

4. Research methodology

To answer the research question, we have prepared a complete set of open innovation benefits and costs in the context of university-industry research collaboration, examining the key related literature. To finalize the list of benefits and costs, we first identified the benefits and costs mentioned in the related literature. For this, we studied 327 selected articles, whose selection procedure was explained in the literature review section. It must be noted that the selected articles are concerned with the benefits and costs of both open innovation and university-industry research collaboration.

Then, we checked if the benefits and costs are relevant to universities when it comes to university-industry research collaboration. To do this, we rated the benefits and costs using a 5-point Likert-type scale (scored 1: "Very low," 2: "Low," 3: "Medium," 4: "High," 5: "Very high"), and if we identified that the relevancy of a benefit or cost is "Very low", we did not select that benefit or cost in the final list. Based on the evaluation, some benefits and costs were selected in the final list. Table 1 presents the final list of benefits and costs of open innovation for universities.

Table 1 The benefits and costs of open innovation for universities concerning their collaboration with industries.

Label	**Type**	**Alternative**	**Source**
Be01	Benefit	Implementing the learnings	(Noh, 2015), (Caputo et al., 2016)
Be02	Benefit	Increased know-how	(Han, 2017)
Be03	Benefit	Accessing specialized infrastructures	(D'este & Perkmann, 2011)
Be04	Benefit	Reduced R&D Costs	(Greco et al., 2019)
Be05	Benefit	Improved teamwork and collaboration abilities	(Suh & Kim, 2012), (Leckel et al., 2020)
Be06	Benefit	Accessing a greater idea and knowledge base	(D'este & Perkmann, 2011)
Be07	Benefit	Being more productive in terms of publication	(Lee and Bozeman, 2005)
Be08	Benefit	Gathering information for teaching	(Lee, 2000)
Be09	Benefit	Accessing talent	(Del Giudice et al., 2018)
Be10	Benefit	Sharing risks of projects	(Vanhaverbeke et al., 2008)
Be11	Benefit	Discovering market needs	(Szutowski, 2018)
Be12	Benefit	Improved brand reputation	(Chesbrough et al., 2014)
Be13	Benefit	Increased commercialization capacity	(Wyckoff & Koreen, 2010)
Be14	Benefit	Sensing and seizing new technological trends	(Grimaldi et al., 2013)
Be15	Benefit	Creating new revenue streams from NPD	(D'Este & Patel, 2007)
Be16	Benefit	Learning from other organizational cultures and their management systems	(Reed et al., 2012)
Be17	Benefit	Increased patents	(Lichtenthaler, 2010), (Ren & Su, 2015), (Marullo et al., 2021)
Be18	Benefit	Keeping the employees engaged	(Jonsson et al., 2015), (Hosseini et al., 2017)
Be19	Benefit	Increased agility	(Cepeda & Arias-Pérez, 2019)
Co01	Cost	Lack of the necessary resources to monitor activities between university and industry	(Manzini et al., 2017)
Co02	Cost	Facing different cultures and terminologies	(Håkansson & Waluszewski, 2007)
Co03	Cost	Increased resistance to change among employees	(Mortara et al., 2010)
Co04	Cost	Difficulty in coordinating the activities between university and industry	(Manzini et al., 2017)
Co05	Cost	Increased possibility of the knowledge leakage	(Salge et al., 2013), (Alberti & Pizzurno, 2017)
Co06	Cost	limiting or causing delays in the publication of scientific articles	(Blumenthal et al., 1996), (Campbell et al., 2000)
Co07	Cost	Increased costs to absorb external knowledge	(Faems et al., 2010)
Co08	Cost	Conflict of interest (different missions)	(Bruneel et al., 2010)

Co09	Cost	Increased employees' resilience due to NIH syndrome (tendency to avoid using the knowledge that organizations do not create themselves)	(Hannen et al., 2019), (de Araújo Burcharth et al., 2014), (Kathoefer & Leker, 2012)
Co10	Cost	Reduced rarity of knowledge assets	(Torkkeli et al., 2009)
Co11	Cost	Paying time costs associated with bureaucracy rules	(Martovoy et al., 2015)
Co12	Cost	Paying extra costs of relationship maintenance	(Fu et al., 2019)
Co13	Cost	loss of focus	(Helm et al., 2019)
Co14	Cost	spending time scouting potential partners	(Locatelli et al., 2021)

Then, we ask the current and emeritus tenure-track faculty of the University of Ottawa to evaluate the benefits and costs of university-industry research collaboration for universities via filling out an online survey. For this purpose, we first ask the faculty members who are on the contact list of the Technology Transfer and Business Enterprise (TTBE) office of the university to fill out the survey, and if we do not receive enough responses, we ask other faculty members of the university to complete the survey. We send the emails randomly and stop the sending process once we receive sufficient responses (15-30). This recruitment approach can cause a higher response rate because the faculty members on the contact list of the TTBE office of the university are more engaged in the subject of the survey, which is "University-Industry research collaboration."

Through the survey, benefits and costs are evaluated in terms of their effects on university performance. In the evolution of performance measurement systems, the concept of going beyond financial measures and defining well-suited non-financial measures has been a significant issue (Kennerley & Neely, 2002). The balanced scorecard (BSC), which Norton and Kaplan have incarnated in the early 1990s (Kaplan & Norton, 1996; Kaplan & Norton, 2010), is outstanding in this concept (Cheng & Humphreys, 2012). Financial, Customer, Internal business processes, and learning and growth are the typical dimensions of BSC (Kaplan & Norton, 2004).

Studying the research works that develop performance measurement criteria for universities based on the BSC approach (e.g. (Al-Hosaini & Sofian, 2015), (Pietrzak et al., 2015), and (Alani et al., 2018)), we have selected four specific criteria corresponding to dimensions of performance presented by the BSC approach. The four selected articles are "skills and knowledge of faculty members", "university research excellence", "university reputation", and "university financial resources such as funds and capital assets". To select these four criteria, we first reviewed the "balanced scorecard in universities" literature and procured a list of thirteen performance measurement criteria. Then, using a 5-point Likert-type scale (scored 1: "Very low," 2: "Low," 3: "Medium," 4: "High," 5: "Very high"), we, the researchers, graded the potential criteria considering two important values. First, we evaluated how much the criteria align with the universities' mission (y Gasset, 2014). Then we evaluated how much they can reflect the type of collaboration between university and industry, which is research-based in this study. Overall, for any performance dimension declared by the BSC approach, we sorted the relevant performance measurement criteria and selected the one that gained the highest score. Table 2 presents the four selected performance measurement criteria and the sources mentioning them.

Table 2 the criteria that have been selected based on the performance concept presented by BSC and the sources mentioning them

Label	**Criterion / indicator**	**Sources**
C01	Skills and knowledge of faculty members	(Zangoueinezhad & Moshabaki, 2011), (Philbin, 2011), (Aljardali et al., 2012), and (Al-Hosaini & Sofian, 2015)
C02	University research excellence	(Aljardali et al., 2012), (Fijałkowska & Oliveira, 2018), (Al-Hosaini & Sofian, 2015), and (Philbin, 2011)
C03	University reputation	(Chen et al., 2006), (Yüksel & Coşkun, 2013), and (Fijałkowska & Oliveira, 2018)
C04	University financial resources such as funds and capital assets	(Pietrzak et al., 2015), (Alani et al., 2018)), (Yüksel & Coşkun, 2013), (Philbin, 2011), and (Al-Hosaini & Sofian, 2015)

After, for each alternative, we ask respondents to answer the question of "Which criteria are influenced highly (or very highly) by the alternative (benefit or cost)?". Respondents can provide more than one answer for each alternative. Table A1 and Table A2 in Appendix 1 present the research questionnaire. Both tables have four columns. In Table A1, the first column shows the label of benefits, and the second column presents the benefit. Also, the third column gives the corresponding question to each benefit. Lastly, the fourth column provides the values that respondents must provide. For example, for the first benefit, we have the following values in different columns:

- The first column (header: label): Be01
- The second column (header: benefit): Implementing the learnings
- The third column (header: related question): In university-industry research collaboration, university researchers can implement their learning. Which of the following items will be improved highly (or very highly) if university researchers implement their learning in industrial research projects?
- The fourth column (header: values): Skills and knowledge of faculty members (Yes/No), University research excellence (Yes/No), University reputation (Yes/No), and University financial resources such as funds and capital assets (Yes/No)).

In Table A2, the first column shows the label of costs, and the second column presents the costs. Also, the third column presents the corresponding question to each cost, and the fourth column provides the values that respondents must provide.

For example, for the first cost, we have the following values in different columns:

- The first column (header: label): Co01
- The second column (header: cost): Lack of the necessary resources to monitor activities between university and industry
- The third column (header: related question): Lack of the necessary resources to monitor activities between university and industry can adversely affect highly (or very highly) which of the following items?
- The fourth column (header: values): Skills and knowledge of faculty members (Yes/No), University research excellence (Yes/No), University reputation (Yes/No), and University financial resources such as funds and capital assets (Yes/No)).

After the survey, we need to organize the benefits and costs of open innovation for universities. When it comes to organizing the alternatives, MCDM methods can be used to rank (Datta et al., 2009), classify/sort (Zopounidis & Doumpos, 2002), or cluster (De Smet, 2014) the alternatives. In the following, we review different approaches, including ranking, classification/sorting, and clustering, and conclude clustering is the best approach for our case.

In the ranking, the individual alternatives get a specific rank in a hierarchy in order of their importance relative to each other (Wilcoxon, 1992). For ranking, we need to integrate the scores of dimensions into a single measure. In this study, the importance is defined based on the effect of an alternative (benefit or cost) on performance that is a multi-dimensional concept (Franco-Santos et al., 2007; Neely, 2005). So no single measure can provide a correct picture of the critical areas of firms (Kaplan & Norton, 2005, 2007), and it makes ranking an inappropriate approach.

As the next approach, one can use classification to organize benefits and costs and compare them with each other. Classification is mainly the systematic arrangement of items in groups already labeled (Hunter, 2017). In our case, the main issue of using the classification approach is the high number of classes that would be at least 16[5] (2^x; x=number of the criteria (5)). This issue (the high number of classes) results in large similarities between classes and dilution of explanation power of classes (Fukunaga & Flick, 1984; Zhuravlev et al., 2019).

As opposed to classification, clustering does not use predefined classes. Clustering uses mathematical models to identify groups according to similarities between items inside a group and dissimilarities between items that belong to different groups (Fung, 2001). Despite the classification, some clustering tools can develop the optimum number of groups (Albalate et al., 2011). Clustering also does not have the shortcoming of using the prioritization approach since there is no need to integrate criteria into a single measure before clustering.

Since we concluded clustering is the best approach for organizing the benefits and costs of open innovation, we use a multi-criteria clustering approach to answer the research question. Multi-criteria clustering works mainly based on a traditional nearest-neighbor recommendation technique (Resnick et al., 1994). However, instead of using, for example, the Pearson correlation coefficient for measuring similarity, it focuses on the similarities of the respondents by using multi-dimensional distance metrics (Nilashi et al., 2015). According to real data-based experiments, Bilge and Kaleli (2014) have shown that using multi-dimensional distance metrics in an MCDM

[5] The minimum number of values for each criterion is two (e.g., (0,1))

context results in more accurate recommendations since decision-makers are considered in multi-aspects of alternatives.

Generally, multi-criteria clustering methods are categorized into two groups: hierarchical clustering and non-hierarchical clustering.

- In hierarchical clustering, methods seek to construct a hierarchy of clusters. There are two general approaches in hierarchical clustering: agglomerative and divisive. The former is also called a bottom-up approach and in which each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. The latter is often called a top-down approach, in which all of the alternatives start in a single comprehensive cluster, and splitting happens recursively as one moves down the hierarchy (Murtagh & Contreras, 2012).

- In non-hierarchical clustering, methods assign data into clusters without any hierarchical structure by maximizing or minimizing some evaluation criteria. Moreover, non-hierarchical clustering methods require decision-makers to decide upon the number of clusters (Saxena et al., 2017).

In this study, we use a hierarchical clustering algorithm for two reasons. First, non-hierarchical algorithms require the decision-maker to decide upon the number of clusters. Since we do not have any idea of the appropriate number of clusters, non-hierarchical clustering methods seem improper for our case. Second, we select the divisive approach over the agglomerative one, considering Roux's (2018) conclusion. Roux (2018) concludes that there is a clear trend for the divisive approaches to be superior to their agglomerative counterpart. Her conclusion is based on comparing Goodman-Kruskal coefficients[6] of 22 different clustering models over 100 random datasets,

In recent years, many scholars have attempted to enhance the extant multi-criteria clustering algorithms. Recently, Ishizaka et al. (2021) have introduced a new divisive hierarchical clustering algorithm that simulates the feasible space of potential clusters in a stochastic environment. Using stochastic algorithms, they could obtain the optimum number of clusters as well as take into account uncertainty and imprecision, such as the ill-determination of weights and the preference thresholds. Concerning the enhancement achieved by the proposed approach by Ishizaka et al. (2021), we use Ishizaka et al.'s (2021) approach in our case study. Ishizaka et al.'s (2021) approach includes three main steps: developing the preference matrix, running the stochastic multi-criteria clustering algorithms, and combining several clustering solutions into a final consensus solution. In the following, we present how we implement these three steps in our study.

According to Ishizaka et al.'s (2021) model, we first develop the preference matrix based on the respondents' ratings to cluster the benefits and costs. For this, Ishizaka et al. (2021) propose to use the PROMETHEE[7] (preference ranking organization method for enrichment evaluation) method. To use the PROMETHEE method, we need to select one of the six preference functions proposed by the method's developers (Brans et al., 1986). In this case, the piece-wise linear function is

[6] In statistics, Goodman and Kruskal's gamma is a measure of rank correlation.
[7] The PROMETHEE method is helpful for complex decision-making problems, especially those with several criteria (Greco et al., 2005), and has a variety of applications in many disciplines (Behzadian et al., 2010; Brans & De Smet, 2016).

chosen because of its popularity and simplicity. The PROMETHEE method results in a preference matrix that shows how much an alternative (benefit or cost) is preferred over another alternative.

Then, we need to use a technique to cluster the alternatives based on the resultant preference matrix. For this, we use a stochastic multi-criteria divisive hierarchical clustering algorithm proposed by Ishizaka et al. (2021). The heart of the technique is a divisive hierarchical clustering technique proposed by (De Smet, 2014); however, it can also find the optimum number of clusters. Moreover, Ishizaka et al.'s (2021) model can deal with uncertainty in real-world decision-making situations such as the ill-determination of weights, the preference thresholds, or even the criteria by applying a stochastic approach.

After running the stochastic model, we have several solutions to the problem. As a result, we need to use a consensus generation method to combine several clustering solutions into a final consensus solution. For yielding the consensus clustering solution, Ishizaka et al. (2021) suggest the usage of the Hybrid Bipartite Graph Formulation (HBGF) developed by (Fern & Brodley, 2004). After reaching the consensus clustering solution, we analyze different clusters and discuss the main benefits and costs of open innovation for universities from different perspectives. Figure 3 shows the main steps of Ishizaka et al.'s (2021) model.

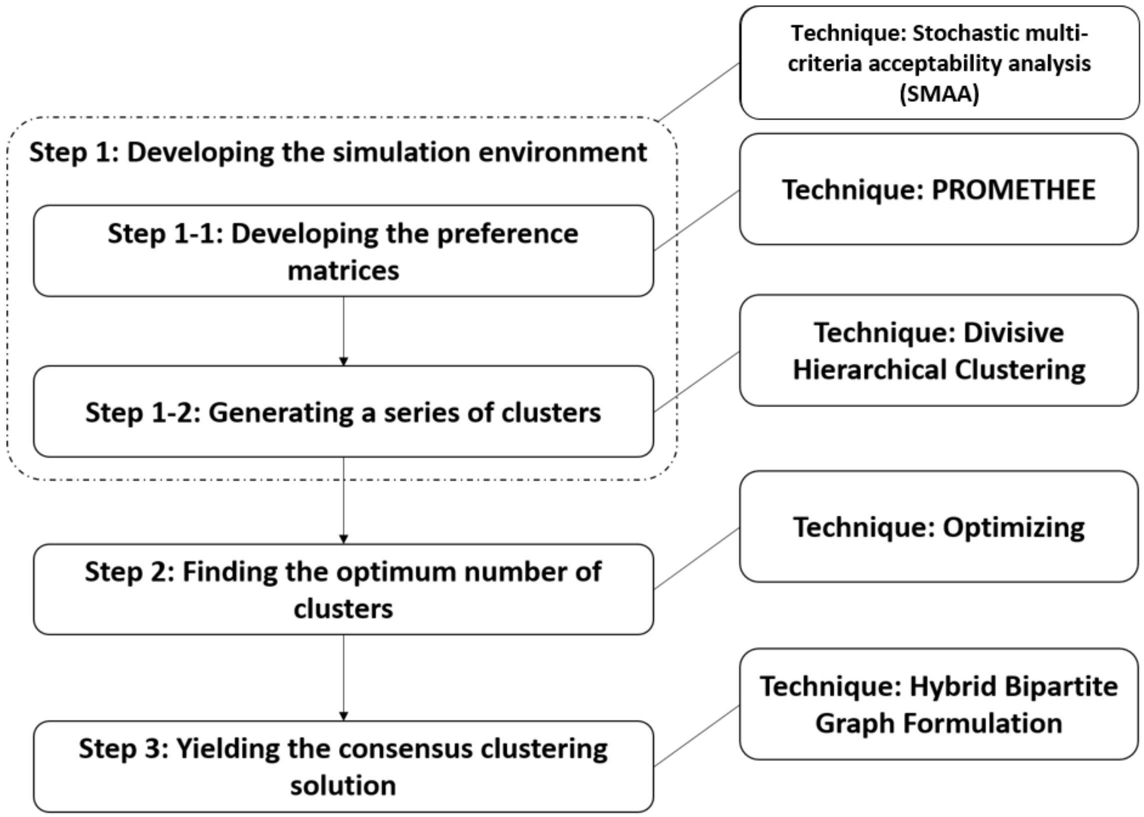

Figure 3 The main steps of Ishizaka et al.'s (2021) model

The technical aspects of the steps have been explained in detail below.

Step1: Developing the simulation environment:

Step 1-1: Developing the preference matrices

The PROMETHEE method is broadly popular in the MCDA community and has a variety of applications among many different disciplines (Behzadian et al., 2010). Here, we discuss only the parts of this method required for the utilized algorithm in this research. Given a set of alternatives $A = \{a_1, \dots, a_n\}$ that would be judged based on criteria $G = \{g_1, \dots, g_m\}$, where $g_i =: A \rightarrow R, j \in J = \{1, \dots, m\}$, for each criterion, $g_j = G$, the PROMETHEE method uses a function that shows the degree of preference a_i over $a_{i'}$ on criterion g_j being a non-decreasing function of $d_j(a_i, a_{i'}) = g_i(a_i) - g_j(a_{i'})$. For using the PROMETHEE method, we need to choose from six functions for each criterion (Deshmukh, 2013). We followed Ishizaka et al.'s (2021) suggestion and, for reasons of simplicity, used the commonly-used piece-wise linear function, which is defined as:

$$P_j(a_i, a_{i'}) = \begin{cases} 0 & \rightarrow if\ d_j(a_i, a_{i'}) \leq\ q_j \\ \dfrac{d_j(a_i, a_{i'}) -\ q_j}{p_{j-}q_j} & \rightarrow\ if\ q_j < d\ _j(a_i, a_{i'}) \leq\ p_j \\ 0 & \rightarrow if\ d_j(a_i, a_{i'}) \geq\ p_j \end{cases}$$

Where p_j and q, are the preference and indifference thresholds set by the decision-maker for each criterion, $g_j = G$. Each criterion g_j is assigned a weight w_j, with $\sum_{j=1}^{m} w_j = 1$ and $w_j > 0$. For each pair of alternatives $(a_i, a_{i'}) \in A\ \times A$, the PROMETHEE method calculates how much a_i is preferred over $a_{i'}$ taking into account all criteria $g_j = G$, as follows:

$\pi(a_i, a_{i'}) = \sum_{j=1}^{m} w_j p(a_i, a_{i'})$, with $\pi(a_i, a_{i'})\ \in [0, 1]$.

Higher values show a greater preference of a_i over $a_{i'}$, and vice versa. Computing $\pi(a_i, a_{i'})$ for every i and i' shapes the $n \times n$ matrix Π, as follows:

$$\Pi = \begin{pmatrix} \pi(a_1, a_1), & \pi(a_1, a_2), & \dots & \pi(a_1, a_n), \\ \pi(a_2, a_1), & \pi(a_2, a_2), & \dots & \pi(a_2, a_n), \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ \pi(a_n, a_1), & \pi(a_n, a_2), & \dots & \pi(a_n, a_n), \end{pmatrix}$$

The diagonal of the $n \times n$ matrix Π is equal to zero and shows how much an alternative a_i in a row, i is preferred to its counterpart $a_{i'}$ in column i'.

For evaluating each action regarding other actions, two scores are calculated (Brans & De Smet, 2016):

- The positive flow: $\phi^+(a_i) = \frac{1}{n-1} \sum_{a_{i'} \in A} \pi(a_i, a_{i'})$; and
- The negative flow: $\phi^-(a_i) = \frac{1}{n-1} \sum_{a_{i'} \in A} \pi(a_{i'}, a_i)$

The positive and negative preference flows are then used to calculate the net preference flow:

$\phi(a_i) = \phi^+(a_i) - \phi^-(a_i)$

In Ishizaka et al.'s (2021) model, the matrix Π is used to cluster the alternatives.

The technical aspects of step 2: Generating a series of clusters

The purpose of multi-criteria clustering is to group actions that have similar preferences. In the algorithm, the preference similarity is given by the preference matrix Π. The preference degree takes values between 0 and 1, where 1 indicates that an action a_i is completely preferred over a_j. Since the matrix is asymmetric, we choose the highest preference degree between the two pairwise comparisons: max $\{\pi(a_i, a_{i'}), \pi(a_{i'}, a_i)\}$.

In the divisive hierarchical clustering algorithm, all objects are first included in a single comprehensive cluster. Then, at each iteration, a cluster is further divided into two. The key point is the rule of dividing or splitting the cluster. Ishizaka et al.'s (2021) algorithm proposes to find those two alternatives, $a_u, a_v \in A$, that are the most opposed (i.e., $\pi(a_u, a_v)$ = max $\{\pi(a_i, a_{i'}), \pi(a_{i'}, a_i)\}$) to form the centroids $a_i \in A$ of the two newly-shaped clusters. Suppose there are two or more equal highest preference degrees. In that case, the decision-maker can select randomly or the first alternative found can be arbitrarily selected (it is done here for simplicity).

For allocating the remaining (n-2) alternatives $a_i \in A$, $i \neq u, v$, we use the preference degree to compare a_i with the two cluster centroids a_u, and a_v . In this regard, the alternatives are assigned to that cluster with the smallest preference distance to the centroid. Since the matrix is asymmetric, we take the highest value of the preference degree, i.e., max $\{\pi(a_i, a_u), \pi(a_u, a_i)\}$ and max $\{\pi(a_i, a_v), \pi(a_v, a_i)\}$. The alternative is then assigned to the cluster with the smallest preference degree. The division procedure is then repeated when a stopping condition is met, such as when a preference degree threshold is met.

The simulation environment to resolve uncertainties:

Like other MCDA methods, the PROMETHEE is inevitably subjective because the decision-maker needs to specify each criterion's weights, preferences, and indifference thresholds. The decision-maker is sometimes unable to specify the exact values for these parameters because they are uncertain that information might be missing or the data are inaccurate. In general, several uncertainties are linked to the identification of the parameters, and the clustering depends on these specific parameters. To resolve these uncertainties, Ishizaka et al. (2021) propose an approach relying on the Stochastic Multiobjective Acceptability Analysis (SMAA) (Corrente et al., 2014) to take into account the full range of solutions to deal with uncertainty and imprecision in real-world decision-making situations.

Dealing with the ill-determination of weights (w_j), preference thresholds (p_j), and the indifference (q_j), we use Monte Carlo simulations in the spaces W, Q, and P, which are given as below:

$$W = \{\boldsymbol{W} = [\boldsymbol{w_1}, \dots, \boldsymbol{w_m}]: \boldsymbol{w_j} > \boldsymbol{0}, \boldsymbol{j} = \boldsymbol{1}, \dots, \boldsymbol{m}, \sum_{\boldsymbol{j}=\boldsymbol{1}}^{\boldsymbol{m}} \boldsymbol{w_j} = \boldsymbol{1}\}$$

$$P = \left\{\boldsymbol{P} = [\boldsymbol{p_1}, \dots, \boldsymbol{p_m}]: \boldsymbol{min}\ \boldsymbol{d_j} \le \boldsymbol{p_j} \le \boldsymbol{max}\ \boldsymbol{d_j}, \qquad \boldsymbol{j} = \boldsymbol{1}, \dots, \boldsymbol{m}, \right\}, \textbf{and}$$

$$Q = \left\{\boldsymbol{q} = [\boldsymbol{q_1}, \dots, \boldsymbol{q_m}]: \boldsymbol{min}\ \boldsymbol{0} \le \boldsymbol{q_j} \le \boldsymbol{p_j}, \qquad \boldsymbol{j} = \boldsymbol{1}, \dots, \boldsymbol{m}, \right\}.$$

Generally, decision-makers have diverse opinions and provide different values for criteria weights and thresholds. For each set of values for criteria weights and thresholds, the spaces W, Q, and P can reasonably be adjusted accordingly, and in this way, many possible solutions can be generated.

In particular, assuming the following m× s matrices:

$$\underset{m\times s}{RW}=\begin{pmatrix} w_{11} & w_{12} & \dots & w_{1s} \\ w_{21} & w_{22} & \dots & w_{2s} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ w_{m1} & w_{m2} & \dots & w_{ms} \end{pmatrix}$$

$$\underset{m\times s}{RP}=\begin{pmatrix} p_{11} & p_{12} & \dots & p_{1s} \\ p_{21} & p_{22} & \dots & p_{2s} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ p_{m1} & p_{m2} & \dots & p_{ms} \end{pmatrix}$$

$$\underset{m\times s}{RQ}=\begin{pmatrix} q_{11} & q_{12} & \dots & q_{1s} \\ q_{21} & q_{22} & \dots & q_{2s} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ q_{m1} & q_{m2} & \dots & q_{ms} \end{pmatrix}$$

Using Monte Carlo simulation, we can collect the set of preferences that summarizes the spaces W, Q, and P where $\mathrm{mc} = 1, \dots,$ s denotes the mc^{th} Monte Carlo simulation:

$$\Pi_{\mathrm{mc}}=\begin{pmatrix} \pi_{mc}(a_1,a_1), & \pi_{mc}(a_1,a_2), & \dots & \pi_{mc}(a_1,a_n), \\ \pi_{mc}(a_2,a_1), & \pi_{mc}(a_2,a_2), & \dots & \pi_{mc}(a_2,a_n), \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ \pi_{mc}(a_n,a_1), & \pi_{mc}(a_n,a_2), & \dots & \pi_{mc}(a_n,a_n), \end{pmatrix}$$

These matrices are input to the clustering algorithm. By changing the values of the weight parameters and thresholds, SMAA-PROMETHEE generates different preference matrices, each of which may result in a different clustering of alternatives. Because we have several different solutions, we need an algorithm to combine them into a final consensus solution. The combination process is performed with ensemble clustering (Fred & Jain, 2005). It should also be noted that a cluster ensemble approach offers more stable and robust solutions compared to a single clustering approach since multiple clustering solutions are combined into a consolidated single clustering solution (Boongoen & Iam-On, 2018; Ghosh & Acharya, 2011).

The technical aspects of step 3: Finding the optimum number of clusters

As explained in the previous step, after developing the preference matrices for the benefits and costs, we need to develop divisive hierarchical clustering models in each trial. In this regard, each trial results in a different number of clusters with different alternatives. To find the optimum number of clusters, we need to use the overall distribution of the number of clusters that are found in all simulations – the simulations with different thresholds and criteria weights. We select the number of clusters with the maximum distribution percentage as the optimum number of clusters. Figure 4 shows how the overall distribution of the number of clusters can be used to select the optimum number of clusters.

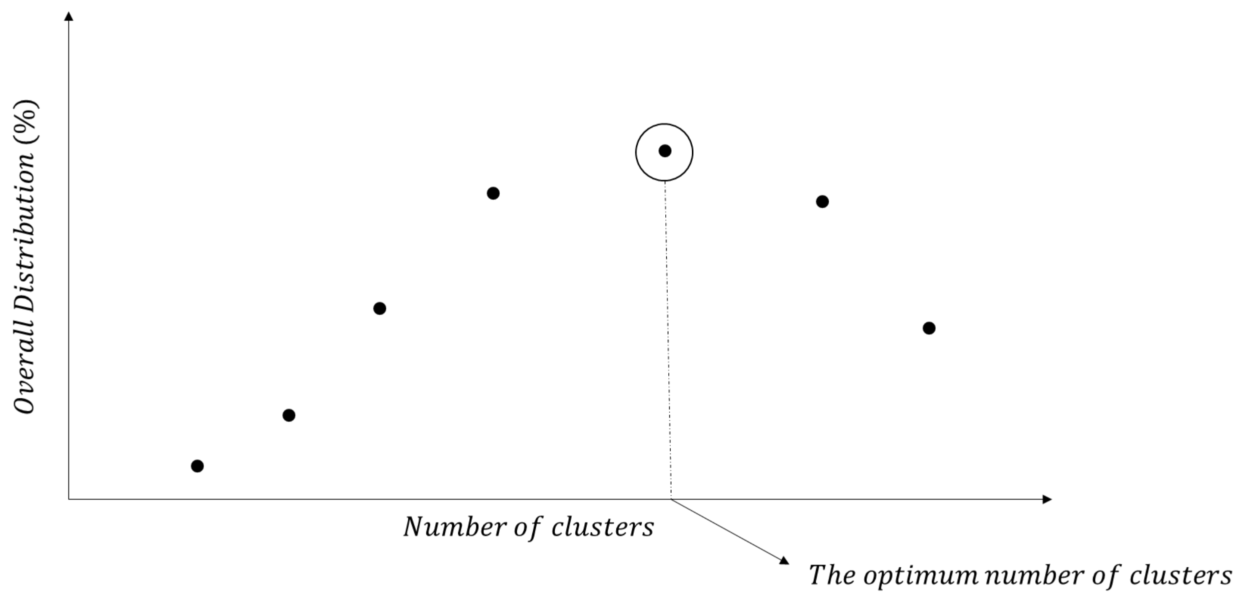

Figure 4 The overall distribution of the number of clusters that can be used to select the optimum number of clusters

Also, we check each trial exclusively and find the threshold at which the maximum number of clusters is equal to the optimum number of clusters. Then we consider that threshold as the optimum threshold value.

The technical aspects of step 4: Yielding the consensus clustering solution

Ensemble Clustering refers to the practice of merging multiple clustering solutions into a final consensus solution. Given a set of clustering solutions $L = \{C^1, \dots, C^s\}$, where each solution has a different number of K^{mc} clusters, ensemble clustering uses a consensus function $\phi(L, K^*)$ to produce a final clustering solution C^* with K^* clusters. In this approach, the decision-maker defines K^* value based on the set of clustering solutions and set it to the k number that frequently happens in the set. Then, Hybrid Bipartite Graph Formulation (HBGF) (Fern & Brodley, 2004) reduces the cluster ensemble problem to a graph partitioning problem.

Description of HBGF: Given a set of clustering solutions $L = \{C^1, \ldots, C^s\}$, HBGF builds a weighted graph $\mathrm{G} = (\mathrm{V}, \lambda)$ where $V = V^L \cup V^A$ and:

- V^L is a set of t vertices, each representing a cluster of the ensemble, and V^A is a set of n vertices, each representing an alternative in A.

- λ is a symmetric matrix in a way that $\lambda(\mathrm{i}, \mathrm{c}) = \lambda(\mathrm{c}, \mathrm{i}) = 0$. If the vertices i and c are both clusters or both alternatives, the $\lambda(\mathrm{i}, \mathrm{c}) = 0$.

- HBGF constructs a matrix Z that connects the alternatives to the clusters, and λ can be written as $\lambda = \begin{pmatrix} 0 & Z^T \\ Z & 0 \end{pmatrix}$. If alternative i is in cluster c, then the entry $Z(i, c)$ takes the value of 1, and 0 otherwise.

Next, the graph is divided into disjoint clusters of vertices by using the well-appreciated spectral partitioning algorithm (Ng et al., 2001). Given a weighted graph $G = (V, \lambda)$ and a number k^*, the spectral partitioning algorithm divides the graph into k^* disjoint clusters of vertices $\boldsymbol{C}^* = \{c_1^*, c_2^*, \ldots, c_{K^*}^*\}$, while $U_K c_K^*$=V. The different divisions of the alternatives can then be used as the final clustering. The objective in partitioning algorithms is to minimize the sum of the weights of the edges crossed by the divisions, which is called the cut: $\lambda(i, c)$ where i and c belong to the different clusters of vertices in the final clustering. In fact, spectral partitioning algorithm uses the normalized cut criterion that measures both the total similarity and dissimilarity between the different groups (Shi & Malik, 2000). Through the spectral partitioning algorithm, first, a diagonal degree matrix D is constructed such that $D(i, i) = \sum_c \lambda(i, c)$ and calculates a normalized weight matrix $\lambda' = D^{-1}\lambda$. Next, concerning the k* largest eigenvectors of λ, a new matrix U is formed by stacking the eigenvectors in columns and normalizing each row to have unit length. After, each row of U is considered as a point and clustered into k* clusters using well-known k*-means algorithm (MacQueen, 1967). Lastly, the alternative i is allocated to cluster c_K^* if and only if row i of the matrix U was allocated to cluster c_K^*. Figure 5 presents how HBGF reduces the ensemble clustering problem to graph partitioning problem. Given there are two different clustering solutions displayed in Figure 5.a and 5.b, HBGF builds the bipartite graph (Figure 5.c) G = (V, λ), where:

- $V = V^L \cup V^A$ where $V^L = \{c_{11}, c_{12}, c_{21}, c_{22}\}$ and $V^A = \{a_1, \dots, a_9\}$, and

- $\lambda = \begin{bmatrix} 0 & Z^T \\ Z & 0 \end{bmatrix}$ where $Z = \begin{array}{c|cccc} & c_{11} & c_{12} & c_{21} & c_{22} \\ \hline a_1 & 1 & 0 & 1 & 0 \\ a_2 & 1 & 0 & 1 & 0 \\ a_3 & 1 & 0 & 1 & 0 \\ a_4 & 1 & 0 & 1 & 0 \\ a_5 & 0 & 1 & 1 & 0 \\ a_6 & 0 & 1 & 1 & 0 \\ a_7 & 0 & 1 & 0 & 1 \\ a_8 & 0 & 1 & 0 & 1 \\ a_9 & 0 & 1 & 0 & 1 \end{array}$

Figure 5.c presents the clusters and alternatives by square and circle, respectively. Each line linking an alternative to a cluster specifies that the alternative belongs to the cluster and has a weight of one. The dashed line displays the cut line and partitioning of the alternatives in V^A into k* = 2 clusters.

As explained above, to generate the consensus clustering solution, we need to use the spectral partitioning algorithm. Given the graph $G = (V, \lambda)$, the spectral partitioning algorithm first computes the degree matrix D, which is a diagonal matrix such that $D(i,i) = \sum_j \lambda(i,j)$. In our sample example, D is:

$$D = \begin{bmatrix} 4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix}$$

Based on D, it then computes a normalized weight matrix $L = D^{-1}W$. In our sample example, L is:

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0.17 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0.33 & 0.33 \\ 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Then, the algorithm finds $L's\ K$ largest eigenvectors $u_1, u_2, \dots, u_K$ to build matrix $U = [u_1, u_2, \dots, u_K]$. The rows of U are then normalized to have unit length. Handling the rows of U as K dimensional embeddings of the graph's vertices, the spectral partitioning algorithm produces the final clustering solution by clustering the embedded points using K-means. In our sample example, the algorithm results in the following consensus clustering solution:

$C^* = \{(a_1,\ a_2, a_3, a_4, a_5), (a_6,\ a_7, a_8, a_9)\}.$

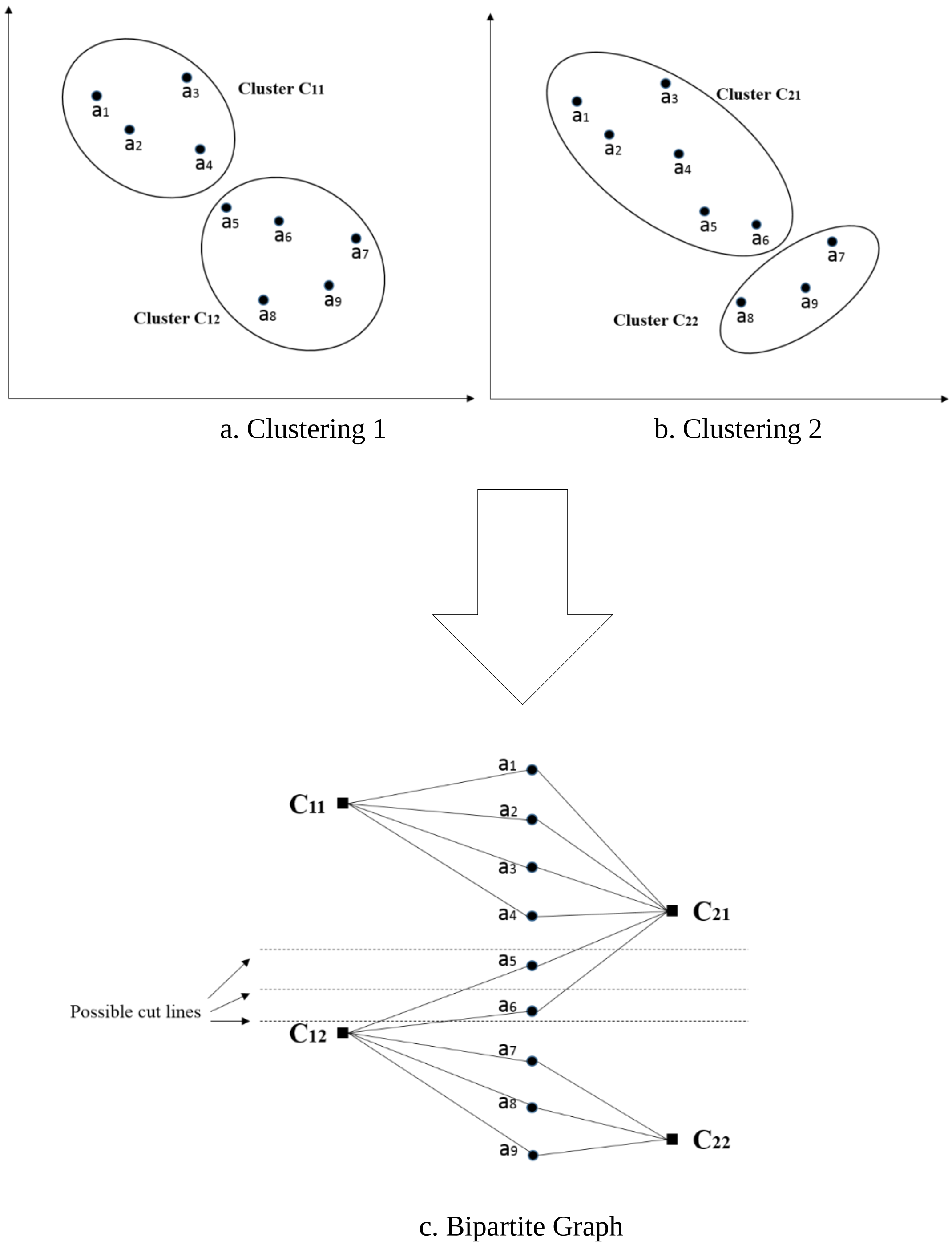

Figure 5 An example of the Hybrid Bipartite Graph Formulation

5. Data retrieval

After sending the invitation email to 247 current and emeritus tenure-track faculties of the University of Ottawa, we received 18 completed responses. Table 3 shows the number of responses provided by different faculties.

Table 3 The number of responses provided by different faculties

Response	Count of Response
Faculty of Engineering	5
Faculty of Science	5
Faculty of Social Sciences	3
Telfer School of Management	5

Then, we coded the answers as 0 or 1, 1 indicating the respondent has selected the alternative (benefit/cost) regarding the criterion, while 0 indicating the respondent has not selected. After, we calculated the arithmetic average of respondents' scores, gaining data scaled from 0 to 1. Tables 4 and 5 present the average respondents' scores for the benefits and costs, respectively.

Table 4 The average respondents' scores for the benefits

Code	Benefit	C1	C2	C3	C4
Be01	Implementing the learnings	0.78	0.44	0.39	0.50
Be02	Increased know-how	0.83	0.61	0.39	0.33
Be03	Accessing specialized infrastructures	0.61	0.78	0.28	0.17
Be04	Reduced R&D Costs	0.00	0.06	0.00	0.56
Be05	Improved teamwork and collaboration abilities	0.56	0.44	0.28	0.17
Be06	Accessing greater idea and knowledge base	0.50	0.72	0.44	0.22
Be07	Being more productive in terms of publication	0.39	0.56	0.83	0.06
Be08	Gathering information for teaching	0.56	0.17	0.56	0.17
Be09	Accessing talent	0.28	0.44	0.50	0.22
Be10	Sharing risks of projects	0.11	0.22	0.11	0.50
Be11	Discovering market needs	0.28	0.22	0.44	0.56
Be12	Improved brand reputation	0.11	0.06	0.89	0.39
Be13	Increased commercialization capacity	0.17	0.11	0.39	0.94
Be14	Sensing and seizing new technological trends	0.50	0.67	0.39	0.56
Be15	Creating new revenue streams from NPD	0.06	0.17	0.22	0.94
Be16	Learning from other organizational cultures and their management systems	0.39	0.39	0.17	0.06
Be17	Increased patents	0.22	0.50	0.61	0.44
Be18	Keeping the employees engaged	0.44	0.67	0.28	0.22
Be19	Increased agility	0.22	0.28	0.39	0.17

Table 5 The average respondents' scores for the costs

Code	Cost	C1	C2	C3	C4
Co01	Lack of the necessary resources to monitor activities between university and industry	0.17	0.50	0.33	0.22
Co02	Facing different cultures and terminologies	0.11	0.22	0.22	0.00
Co03	Increased resistance to change among employees	0.39	0.44	0.39	0.11
Co04	Difficulty to coordinate the activities between university and industry	0.11	0.28	0.39	0.22
Co05	Increased possibility of the knowledge leakage	0.11	0.22	0.72	0.11
Co06	limiting or causing delays in the publication of scientific articles	0.17	0.44	0.56	0.06
Co07	Increased costs to absorb external knowledge	0.11	0.06	0.11	0.44
Co08	Conflict of interest (different missions)	0.06	0.50	0.33	0.22
Co09	Increased employees' resilience due to NIH syndrome (tendency to avoid using the knowledge that organizations do not create themselves)	0.39	0.39	0.17	0.00
Co10	Reduced rarity of knowledge assets	0.22	0.11	0.39	0.28
Co11	Paying time costs associated with bureaucracy rules	0.22	0.44	0.17	0.50
Co12	Paying extra costs of relationship maintenance	0.17	0.28	0.17	0.50
Co13	loss of focus	0.28	0.44	0.28	0.17
Co14	spending time scouting potential partners	0.06	0.17	0.11	0.22

6. Model development

Step 1: Developing the simulation environment

According to the first step of Ishizaka et al.'s (2021) model, we used the Monte Carlo simulation to generate different series of clusters for different randomly generated criteria weights. We drew 10,000[8] criteria weight sets from a uniform distribution in the simulation environment. We generated a specific reference matrix for each criteria weight set and the related clusters to that

[8] Suggested by Tervonen and Lahdelma (2007) as the appropriate number of simulations for stochastic multi-criteria.

specific reference matrix. We performed the steps mentioned above five times[9] for different threshold values (ε = 0.20, 0.25, 0.30, 0.35, 0.40). Tables 6 and 7 present the preference matrices under the condition that all criteria weights are equal to each other[10] (w_j=0.25).

[9] Proposed by Ishizaka et al. (2021).

[10] Since, a specific reference matrix was developed in each simulation trial, we preferred to just present the preference matrices that were developed under the condition that all criteria weights are equal.

Table 6 The preference matrices of the benefits under the condition that all criteria weights are equal to each other (w_j=0.25)

	Be1	**Be2**	**Be3**	**Be4**	**Be5**	**Be6**	**Be7**	**Be8**	**Be9**	**Be10**	**Be11**	**Be12**	**Be13**	**Be14**	**Be15**	**Be16**	**Be17**	**Be18**	**Be19**
Be1	0.00	0.28	0.07	0.07	0.15	0.11	0.24	0.09	0.25	0.05	0.11	0.13	0.07	0.27	0.00	0.28	0.07	0.07	0.15
Be2	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.05	0.03	0.01	0.03	0.03	0.00	0.12	0.00	0.00	0.00	0.00	0.00
Be3	0.22	0.42	0.00	0.25	0.26	0.22	0.44	0.31	0.21	0.18	0.27	0.34	0.16	0.48	0.22	0.42	0.00	0.25	0.26
Be4	0.03	0.24	0.07	0.00	0.07	0.10	0.19	0.08	0.27	0.02	0.13	0.13	0.10	0.23	0.03	0.24	0.07	0.00	0.07
Be5	0.23	0.37	0.20	0.20	0.00	0.13	0.39	0.28	0.40	0.21	0.33	0.33	0.27	0.42	0.23	0.37	0.20	0.20	0.00
Be6	0.13	0.31	0.10	0.17	0.07	0.00	0.36	0.22	0.27	0.14	0.23	0.25	0.17	0.39	0.13	0.31	0.10	0.17	0.07
Be7	0.13	0.27	0.20	0.13	0.20	0.24	0.00	0.18	0.27	0.10	0.00	0.00	0.17	0.18	0.13	0.27	0.20	0.13	0.20
Be8	0.00	0.24	0.07	0.03	0.10	0.11	0.19	0.00	0.25	0.05	0.11	0.13	0.07	0.18	0.00	0.24	0.07	0.03	0.10
Be9	0.18	0.25	0.00	0.24	0.25	0.18	0.30	0.27	0.00	0.17	0.14	0.20	0.09	0.34	0.18	0.25	0.00	0.24	0.25
Be10	0.11	0.36	0.10	0.13	0.19	0.18	0.26	0.20	0.30	0.00	0.13	0.18	0.13	0.34	0.11	0.36	0.10	0.13	0.19
Be11	0.21	0.42	0.24	0.28	0.36	0.32	0.21	0.31	0.31	0.18	0.00	0.07	0.20	0.37	0.21	0.42	0.24	0.28	0.36
Be12	0.17	0.36	0.24	0.21	0.29	0.27	0.14	0.26	0.30	0.16	0.00	0.00	0.20	0.31	0.17	0.36	0.24	0.21	0.29
Be13	0.09	0.30	0.03	0.16	0.20	0.16	0.29	0.18	0.17	0.09	0.11	0.18	0.00	0.32	0.09	0.30	0.03	0.16	0.20
Be14	0.00	0.13	0.07	0.00	0.07	0.10	0.01	0.00	0.13	0.01	0.00	0.00	0.03	0.00	0.00	0.13	0.07	0.00	0.07
Be15	0.00	0.28	0.07	0.07	0.15	0.11	0.24	0.09	0.25	0.05	0.11	0.13	0.07	0.27	0.00	0.28	0.07	0.07	0.15
Be16	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.05	0.03	0.01	0.03	0.03	0.00	0.12	0.00	0.00	0.00	0.00	0.00
Be17	0.22	0.42	0.00	0.25	0.26	0.22	0.44	0.31	0.21	0.18	0.27	0.34	0.16	0.48	0.22	0.42	0.00	0.25	0.26
Be18	0.03	0.24	0.07	0.00	0.07	0.10	0.19	0.08	0.27	0.02	0.13	0.13	0.10	0.23	0.03	0.24	0.07	0.00	0.07
Be19	0.23	0.37	0.20	0.20	0.00	0.13	0.39	0.28	0.40	0.21	0.33	0.33	0.27	0.42	0.23	0.37	0.20	0.20	0.00

Table 7 The preference matrices of the costs under the condition that all criteria weights are equal to each other (w_j=0.25)

	Co1	**Co2**	**Co3**	**Co4**	**Co5**	**Co6**	**Co7**	**Co8**	**Co9**	**Co10**	**Co11**	**Co12**	**Co13**	**Co14**
Co1	0.00	0.28	0.07	0.07	0.15	0.11	0.24	0.09	0.25	0.05	0.11	0.13	0.07	0.27
Co2	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.05	0.03	0.01	0.03	0.03	0.00	0.12
Co3	0.22	0.42	0.00	0.25	0.26	0.22	0.44	0.31	0.21	0.18	0.27	0.34	0.16	0.48
Co4	0.03	0.24	0.07	0.00	0.07	0.10	0.19	0.08	0.27	0.02	0.13	0.13	0.10	0.23
Co5	0.23	0.37	0.20	0.20	0.00	0.13	0.39	0.28	0.40	0.21	0.33	0.33	0.27	0.42
Co6	0.13	0.31	0.10	0.17	0.07	0.00	0.36	0.22	0.27	0.14	0.23	0.25	0.17	0.39
Co7	0.13	0.27	0.20	0.13	0.20	0.24	0.00	0.18	0.27	0.10	0.00	0.00	0.17	0.18
Co8	0.00	0.24	0.07	0.03	0.10	0.11	0.19	0.00	0.25	0.05	0.11	0.13	0.07	0.18
Co9	0.18	0.25	0.00	0.24	0.25	0.18	0.30	0.27	0.00	0.17	0.14	0.20	0.09	0.34
Co10	0.11	0.36	0.10	0.13	0.19	0.18	0.26	0.20	0.30	0.00	0.13	0.18	0.13	0.34
Co11	0.21	0.42	0.24	0.28	0.36	0.32	0.21	0.31	0.31	0.18	0.00	0.07	0.20	0.37
Co12	0.17	0.36	0.24	0.21	0.29	0.27	0.14	0.26	0.30	0.16	0.00	0.00	0.20	0.31
Co13	0.09	0.30	0.03	0.16	0.20	0.16	0.29	0.18	0.17	0.09	0.11	0.18	0.00	0.32
Co14	0.00	0.13	0.07	0.00	0.07	0.10	0.01	0.00	0.13	0.01	0.00	0.00	0.03	0.00

As is stated in Ishizaka et al.'s (2021) model, in each simulation trial, after developing the preference matrices for the benefits and costs, we need to develop divisive hierarchical clustering models. Each trial results in a different number of clusters with a different set of alternatives. Table 8 and Figure 6 show how the distribution of the number of clusters of the benefits changes at different threshold values.

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Table 8 The distribution of the number of clusters of the benefits at different threshold values

# of clusters	The distribution of the number of clusters of the benefits (%)				
	ε=0.20	ε=0.25	ε=0.30	ε=0.35	ε=0.40
2	0.0%	0.0%	0.7%	27.3%	70.1%
3	0.0%	0.0%	18.5%	51.6%	28.5%
4	1.0%	35.3%	69.6%	20.7%	1.4%
5	20.6%	55.3%	11.1%	0.4%	0.0%
6	46.4%	9.0%	0.2%	0.0%	0.0%
7	27.5%	0.4%	0.0%	0.0%	0.0%
8	4.4%	0.0%	0.0%	0.0%	0.0%
9	0.1%	0.0%	0.0%	0.0%	0.0%

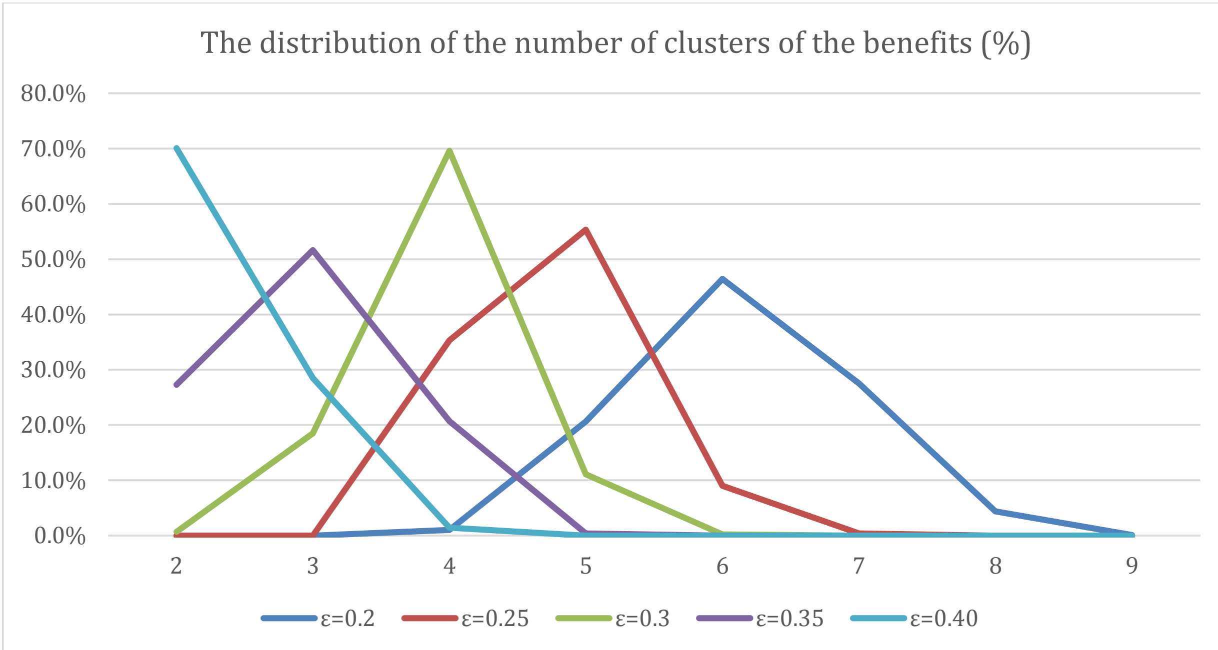

Figure 6 The distribution of the number of clusters of the benefits at different threshold values

Table 9 and Figure 7 show how the distribution of the number of clusters of the costs changes at different threshold values.

Table 9 The distribution of the number of clusters of the benefits at different threshold values

# of clusters	The distribution of the number of clusters of the costs (%)				
	ε=0.20	ε=0.25	ε=0.30	ε=0.35	ε=0.40
2	0.0%	0.0%	0.0%	12.7%	57.8%
3	0.0%	0.6%	23.1%	64.2%	38.4%
4	2.7%	25.0%	54.7%	22.5%	3.8%
5	26.8%	49.1%	19.2%	0.6%	0.0%
6	38.9%	22.8%	3.1%	0.0%	0.0%
7	25.4%	2.4%	0.0%	0.0%	0.0%
8	5.8%	0.0%	0.0%	0.0%	0.0%
9	0.4%	0.0%	0.0%	0.0%	0.0%

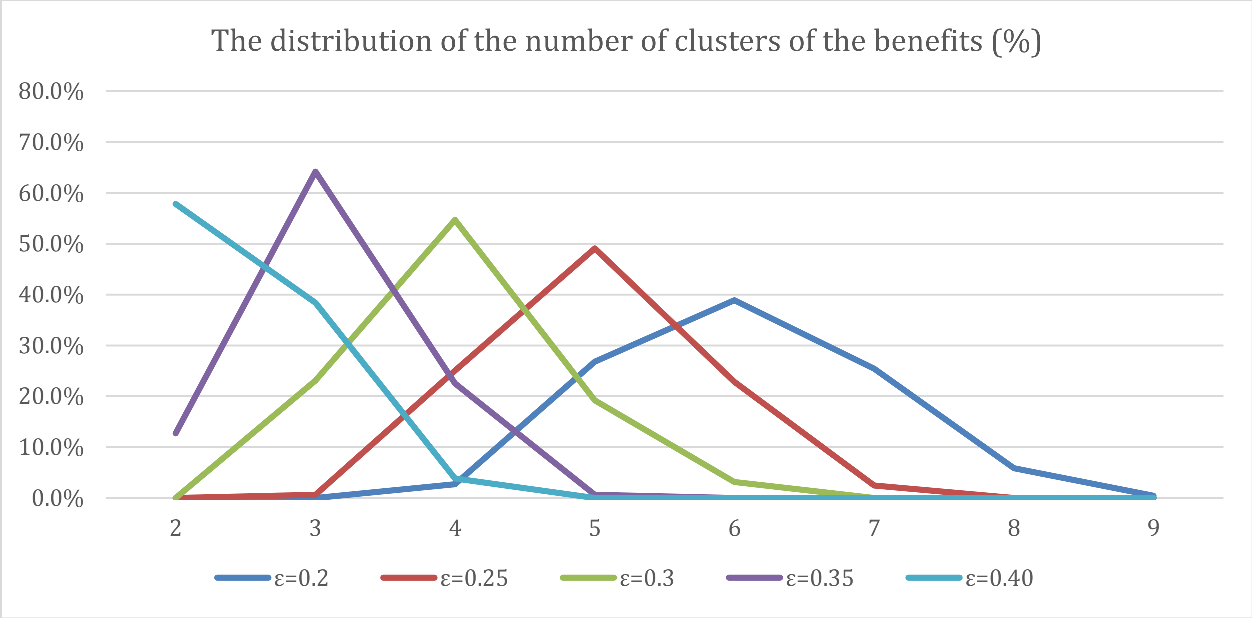

Figure 7 The distribution of the number of clusters of the costs at different threshold values.

Step 2: Finding the optimum number of clusters

To find the optimum number of clusters, we needed to check the overall distribution of the number of clusters found in all simulations. For this, we calculated the average of the distribution of the number of clusters (in percent) that are found for different threshold values. Then, concerning all simulation trials, we selected the number of clusters with the highest distribution percentage as the optimum number of clusters. Figures 8 and 9 show the overall distribution of the number of clusters for the benefits and costs, respectively. With respect to the benefits, the highest distribution percentage of distribution and the optimum number of clusters are 25.6% and 4, respectively (Figure 8). Regarding the costs, the highest distribution percentage of distribution and the optimum number of clusters are 25.3% and 3, respectively (Figure 9).

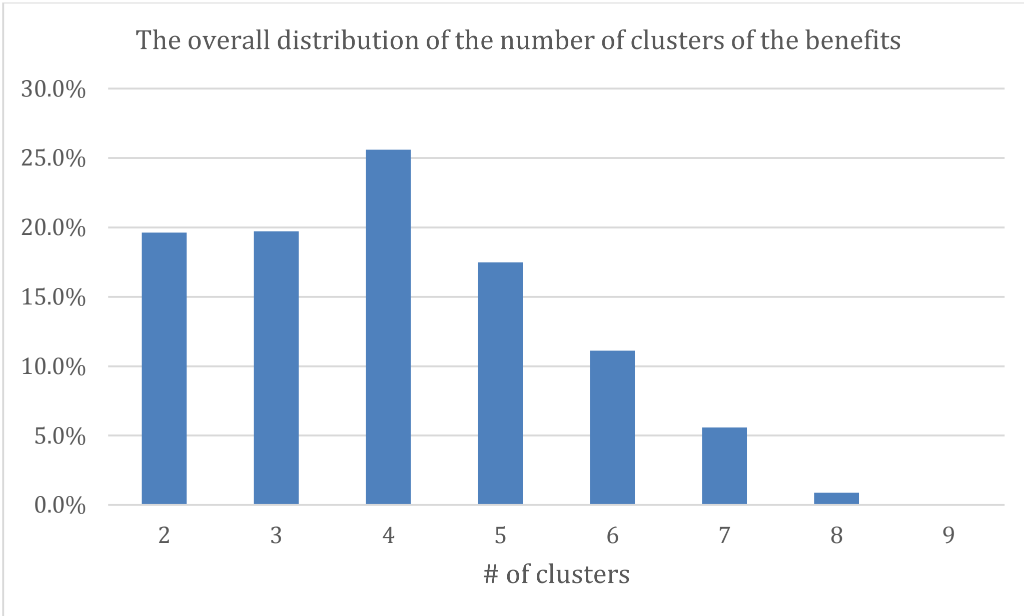

Figure 8 The overall distribution of the number of clusters of the benefits

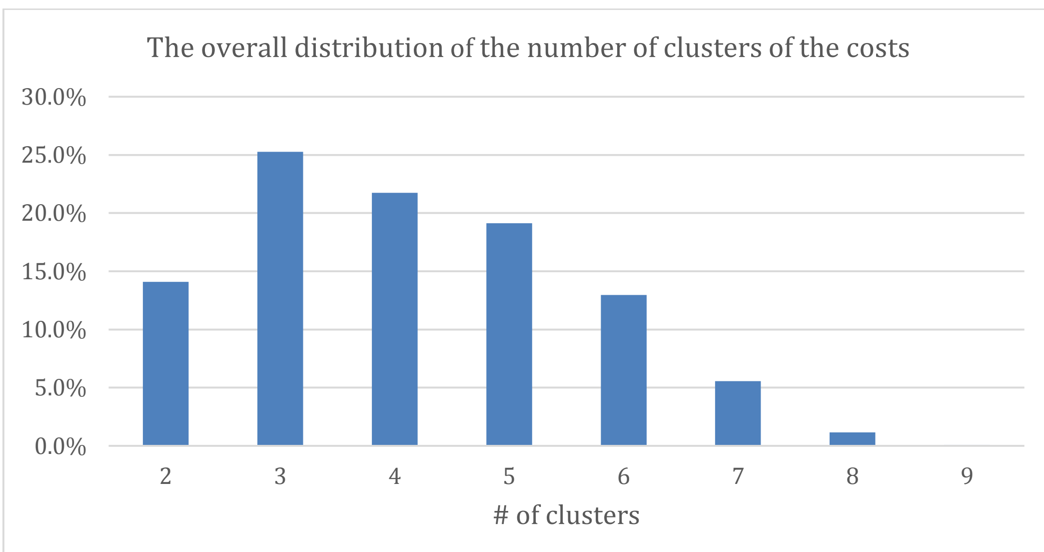

Figure 9 The overall distribution of the number of clusters of the costs

Step 3: Yielding the consensus clustering solution

By looking at the distributions obtained through different ε values, we ended up with the highest overall distribution backing the k=4 choice of ε = 0.3 for the benefits, and the k=3 choice of ε =

0.35 for the costs. In the simulation environment for the benefits, out of 10,000 trials for ε = 0.3, 6,962 trials generated 4 clusters. Also, with respect to the costs, out of 10,000 trials for ε = 0.35, 6,422 trials generated 3 clusters.

According to Ishizaka et al.'s (2021) model, we used the Hybrid Bipartite Graph Formulation method to combine different clustering solutions into a consensus solution. Although we used the application R to develop the models in this study, here, we have used MATLAB for the development of the HBGF model (see appendix 2). In fact, there is no validated coding in the R language for the HBGF method (to our best knowledge); however, a validated coding in MATLAB[11] is presented by (Fern & Brodley, 2004).

As explained in section 4, the Hybrid Bipartite Graph Formulation method uses the Spectral Partitioning algorithm and K-means to generate Cluster-IDs. Tables 10 and 11 show how the benefits and costs have been assigned to a cluster ID. The cluster-ID 1 and 4 refer to the highest and lowest hierarchy/importance cluster, respectively

Table 10 The benefits that have been assigned to a cluster-ID

Code	**Benefit**	**Cluster-ID**
Be01	Implementing the learnings	1
Be02	Increased know-how	1
Be03	Accessing specialized infrastructures	1
Be06	Accessing a greater idea and knowledge base	1
Be14	Sensing and seizing new technological trends	1

[11] https://web.engr.oregonstate.edu/~xfern/HBGF_spec.m

Be18	Keeping the employees engaged	1
Be05	Improved teamwork and collaboration abilities	2
Be07	Being more productive in terms of publication	2
Be08	Gathering information for teaching	2
Be09	Accessing talent	2
Be17	Increased patents	2
Be11	Discovering market needs	3
Be12	Improved brand reputation	3
Be13	Increased commercialization capacity	3
Be15	Creating new revenue streams from NPD	3
Be04	Reduced R&D Costs	4
Be10	Sharing risks of projects	4
Be16	Learning from other organizational cultures and their management systems	4
Be19	Increased agility	4

Table 11 The costs that have been assigned to a cluster-ID

code	**Cost**	**Cluster-ID**
Co01	Lack of the necessary resources to monitor activities between university and industry	1
Co03	Increased resistance to change among employees	1
Co08	Conflict of interest (different missions)	1
Co09	Increased employees' resilience due to NIH syndrome (tendency to avoid using the knowledge that organizations do not create themselves)	1
Co11	Paying time costs associated with bureaucracy rules	1
Co13	loss of focus	1
Co04	Difficulty to coordinate the activities between university and industry	2
Co05	Increased possibility of the knowledge leakage	2
Co06	limiting or causing delays in the publication of scientific articles	2

Co02	Facing different cultures and terminologies	3
Co07	Increased costs to absorb external knowledge	3
Co10	Reduced rarity of knowledge assets	3
Co12	Paying extra costs of relationship maintenance	3
Co14	spending time scouting potential partners	3

Figures 10 and 11 show the arithmetic average of respondents' scores for the benefits and costs in each cluster. They show that the average of respondents' scores in the first cluster is the largest, and the average score of the clusters decreases while the cluster-ID increases. It is because we have used a hierarchical clustering method that shapes ordered clusters.

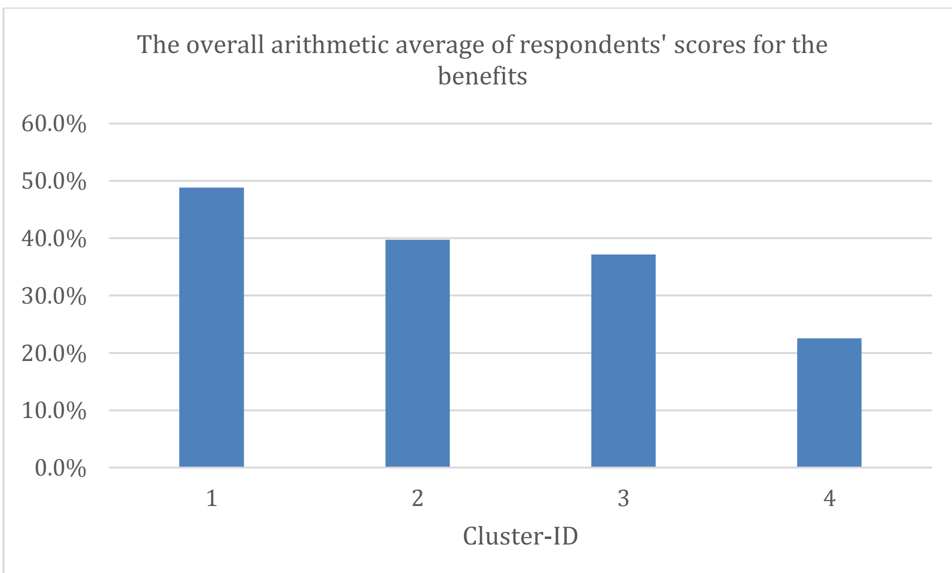

Figure 10 The overall arithmetic average of respondents' scores for the benefits in each cluster

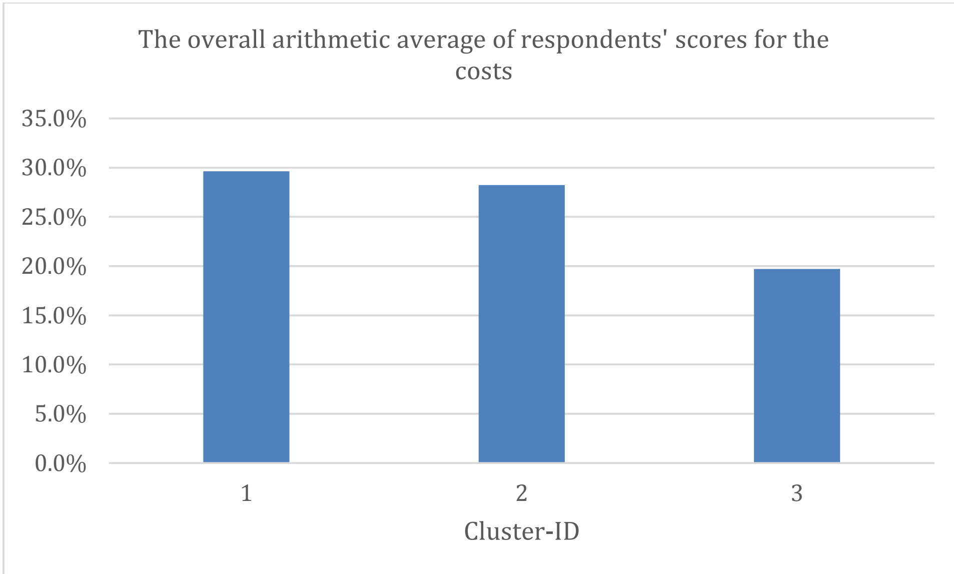

Figure 11 The overall arithmetic average of respondents' scores for the costs in each cluster

Moreover, Figures 12 and 13 detail the arithmetic average of respondents' scores for the benefits and costs in each cluster.

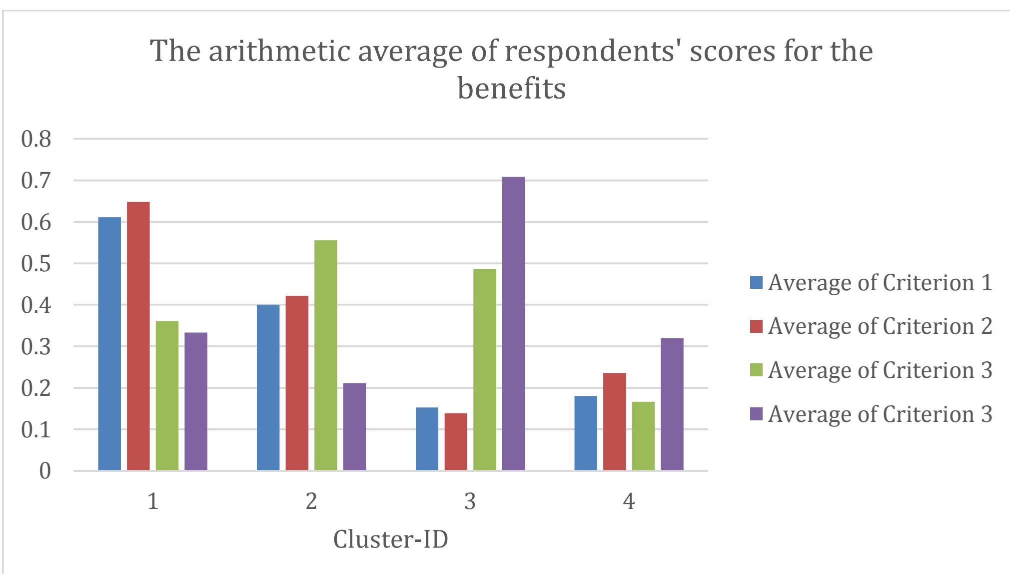

Figure 12 The arithmetic average of respondents' scores for the benefits in each cluster

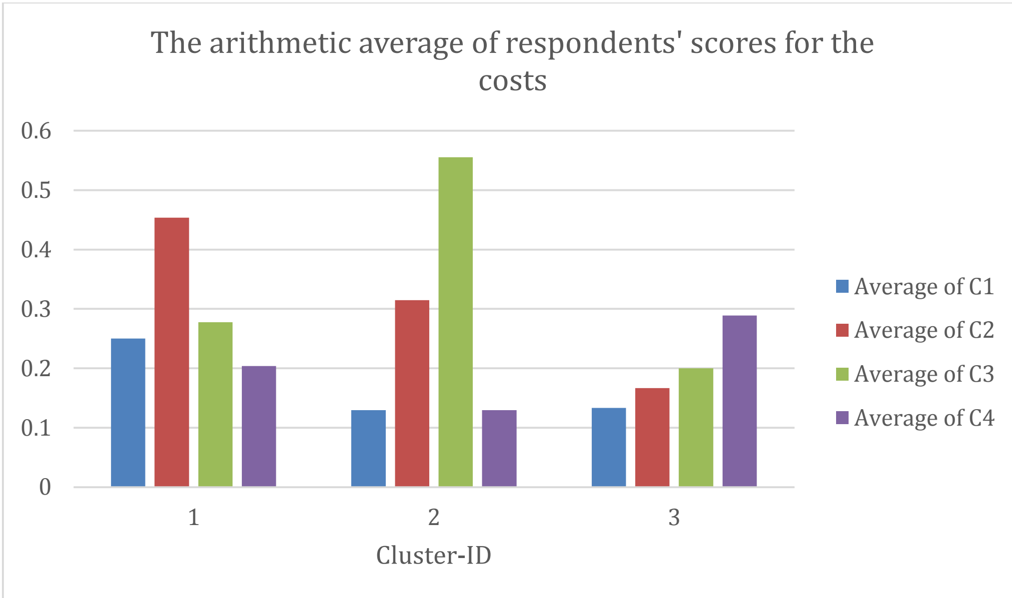

Figure 13 The arithmetic average of respondents' scores for the costs in each cluster

7. Discussion

We are dealing with a volatile and competitive environment that necessitates organizations to innovate at a fast pace to meet the demands of the global market (Magdaleno et al., 2011). Meanwhile, collaboration has become an imperative instrument to overcome the organizational challenges fostered by new economies of scale (Alonso et al., 2010; Demircioglu & Audretsch, 2019). In this regard, there are accelerated efforts to encourage collaborations, particularly research collaboration between universities and industry (Awasthy et al., 2020). However, it is still challenging for universities to identify the best practices to follow to establish a productive collaboration with industrial partners, resulting in the ineffectiveness of university-industry collaboration. This has led to the increasing need for establishing some guidelines to support the success of research collaboration between universities and industry.

With reference to Figures 12 and 13, one can see that the highest averages of respondents' scores for criterion 1 (Skills and knowledge of faculty members) and criteria 2 (university research excellence) belong to cluster one, while the highest averages of respondents' scores for criteria 3 (university reputation) and criteria 4 (university financial resources such as funds and capital assets) do not belong to this cluster. It infers that criteria 1 and 2 have been concerned more than two other criteria in defining the most important cluster for both the benefits and costs. This finding can be used to explore the main intentions of academics to engage in university-industry collaboration. It would be important because the motives of academics to engage in university-industry collaboration still remain under-researched (Compagnucci & Spigarelli, 2020).

While a standpoint explains that university researchers collaborate with industry mainly because of economic reasons and commercializing their knowledge (Cunningham & Link, 2015; Lach & Schankerman, 2008), another standpoint maintains that economic reasons rank as the least important motivation for engaging with industry and knowledge-related and research-related reasons dominate (Bukhari et al., 2021; D'este & Perkmann, 2011). Since criteria 1 and 2 are about knowledge-related and research-related factors and are dominant in determining the most important benefits and costs from the viewpoint of decision-makers, we can conclude that our finding supports the latter standpoint.

Furthermore, we highlighted the most important benefits and costs of university-industry research collaboration in view of different dimensions of performance. It helps researchers and decision-makers to obtain a guiding understanding and setting agendas of university-industry research collaboration. The results obtained through the cluster analysis indicate that the most important benefits of university-industry research collaboration for universities are implementing the learnings, increased know-how, accessing specialized infrastructures, accessing a greater idea and knowledge base, sensing and seizing new technological trends, and keeping the employees engaged. In addition, the results show that the most important costs are the lack of necessary resources to monitor activities between university and industry, an increased resistance to change among employees, conflict of interest (different missions), an increased employees' tendency to avoid using the knowledge that they do not create themselves, paying time costs associated with bureaucracy rules, and loss of focus. In the following, we explore the most important benefits of university-industry research collaboration in more detail.

Implementing the learnings: Constructivist theories maintain that learning occurs when individuals assimilate new knowledge with practice (Vygotzky, 1978). This approach recognizes learning as a process of becoming and explores how an idea comes into being, resulting in evidence-informed educational practice (de Carvalho-Filho et al., 2020). When it comes to implementing learning, learning can be fostered in three ways: learning by doing, learning by observing, and learning by reflecting on experience (Steinert, 2010). Implementing knowledge, particularly through collaboration with other organizations and partners, can give researchers new insights and advance innovation (Iskanius & Pohjola, 2016). In this regard, it is proposed that implementing knowledge intensifies university-industry collaboration, and university knowledge should be deployed effectively in industries, and new methods are needed for this purpose (Siegel et al., 2004). Implementing learnings by university researchers is very important for industrial firms to attain scientific knowledge and basic research inputs for innovation (Kodama, 2008) and get a broader view (Iskanius & Pohjola, 2016). It is recommended that people in universalities and industries use appropriate strategies to implement their knowledge (Iskanius & Pohjola, 2016).

In addition, it can be inferred that university-industry research collaboration equips university researchers with meta-competencies and help them to go beyond cognitive knowledge. In fact, universities experience a transition from transferring knowledge to developing individual potentials through the medium of constructivist learning (Scheer et al., 2012). The findings of this study clarify that implementing the learnings is one of the most important benefits of university-industry research collaboration, and universities need to invest in this benefit exclusively. In this regard, future studies should contribute to the research on university-industry collaboration and add to the understanding of different types of learning and particularity implemented learnings. These studies also should consider that the findings for each discipline may be exclusive.

Increased know-how: Experience is a means of learning (Huber, 1991). Know-how is about developing specialized knowledge through experience and using this knowledge to gain more benefits (Simonin, 1997). Universities need to develop collaborative know-how, relying on the experiences accumulated through collaboration with industry. In addition, more interactions between universities and industrial firms teach gaps between these two types of organizations and result in better mutual understanding (Bellini et al., 2019). It has been maintained that collaborative know-how can positively affect the tangible and intangible benefits earned from university-industry collaboration (Bellini et al., 2019).

Know-how is a component of university-industry research collaboration and is a valuable asset that can be transferred into economic prosperity (Bellini et al., 2019). It has been concluded that increased know-how acts as an effective mediating mechanism and helps universities fully benefit from collaboration with industry. The literature emphasizes the importance of increased know-how, which agrees with our findings. Although a few studies have emphasized the important role of collaborative know-how in university-industry collaboration, the literature still requires some more insights that more detailed models can achieve. Insights such as how university-industry collaboration affects know-how from universities' point of view and how to increase it (Bellini et al., 2019; Bellucci & Pennacchio, 2016).

Accessing specialized infrastructures: A number of studies find that infrastructure is critical for performance and growth (Aterido et al., 2011; Harrison & Thiel, 2017). With the advent of information technology, digitalization, and many sophisticated technologies in recent decades, specialized and technological infrastructures have been a dominant element in competitiveness (Freeman, 2004). In certain industries, particularly high-tech and information technology industries, specialized and technological infrastructure form the primary basis for competition (Miller, 2004). University-industry research collaboration allows university researchers to access these infrastructures and conduct research on the cutting edge. Universities can also use specialized infrastructures to obtain operational flexibility and tactical flexibility. However, they still need to obtain the related technological know-how and ability to take action in response to variability in the external environment (Chedid et al., 2020).

In general, sharing existing specialized and technological infrastructures to respond to emerging needs can improve the quality of university-industry collaboration relationships (Ehrismann & Patel, 2015). Interestingly, it is stated that sharing core facilities between universities and industries can itself result in a productive collaboration (Kauppila et al., 2015). It is recommended for future researchers to investigate strategies, policies, and frameworks promoting the sharing of specialized infrastructures between universities and industries, particularly when it comes to university-industry research collaboration (Kauppila et al., 2015; Zhua et al.).

Accessing a greater idea and knowledge base: Over the recent decades, the external knowledge flows have been considered an important driver of the innovation process within organizations (Chedid et al., 2020). The idea of the generation of new knowledge fully internally is mostly abandoned (Gans & Stern, 2003), and the borderlines between the firm's knowledge stock and external knowledge stock are blurred (Von Krogh et al., 2012). The outside knowledge flows expands a firm's knowledge base and provides access to new ideas that support the generation of new products and technologies (Bierly III et al., 2009). It also should be noted that technology transfer is always associated with knowledge transfer since the technologies include substantial tacit and explicit knowledge content (Kodama, 2008).

University-industry research collaboration has been widely considered a prominent way of accessing a source of knowledge and new ideas (Melnychuk et al., 2021). Several studies indicate that, within university-industry collaborations, universities' absorptive capacity[12] and also using intermediaries are critical for absorbing external knowledge, particularly tacit knowledge

[12] Absorptive capacity has been defined as "a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990).

(Kodama, 2008). In this regard, using knowledge management mechanisms, including formal and informal, is necessary for universities to achieve the most out of collaboration with industry (Secundo et al., 2019), and our findings support it. The external knowledge base available to a university depends on several factors such as the discipline, social ties, nature of the knowledge, and the approaches toward intellectual property rights (Chedid et al., 2020). Therefore, future research is needed to better understand university-industry collaboration through exploring the procedure of accessing external knowledge by universities.

Sensing and seizing new technological trends: Discovering new technological opportunities and responding to environmental changes are critical for strategic performance. Over the years, universities and industrial firms have been considered research centers that seek to collaborate with each other to create innovative products. This link has a powerful engine of technological development for universities and industries through sensing and seizing new technological trends (Wirsich et al., 2016). There are different methods that universities can use to capture new technologies from industry, including licensing, support contracts, joint ventures, strategic alliances, and equipment acquisition (Bower, 2018). Furthermore, universities establish technology transfer offices to act as a channel between academia and industry and facilitate the process of technology transfer (Young, 2007). It should be emphasized that our findings support the mission of technology transfer offices and accordingly attest to the importance of their existence.

Many works have been done in the literature to better understand how sensing and seizing new technological trends occur during university-industry research collaboration; however, the literature demands more work because of the numerous unknowns in this concept (Arenas & González, 2018). In future works, researchers can explore different models, use different case studies, and describe the basic elements regarding the issue of sensing and seizing new technological trends by universities in university-industry research collaboration.

Keeping the employees engaged: The term "engagement" refers to three constructs: 1) psychological state of involvement, commitment, and attachment, 2) performance status such as prosocial and organizational citizenship behavior, and 3) disposition such as positive affect, or some amalgamation of the above three constructs (Macey & Schneider, 2008). The literature has addressed that organizations with engaged employees have higher shareholder returns, productivity, and stakeholders' satisfaction (Crawford et al., 2010; Harter et al., 2002). Two main beliefs explain the motivation of academic researchers to engage in university-industry research collaboration. The first is that university researchers engage with industry to commercialize their knowledge. On the other hand, the second assumption attributes the motives of engagement to knowledge-related and research-related reasons and considers the least important for economic reasons (D'este & Perkmann, 2011). Having confidence in each belief shapes decision-makers' attributes toward the mechanisms that can be applied to promote university researchers in university-industry collaboration (Tartari et al., 2014).

It has been proved that there is a close relationship between academic engagement and commercialization (Perkmann et al., 2013). Universities can use several means to improve academic engagement, including encouraging teamwork, circulating mission and goals statements, and supporting the growth of employees (Perkmann et al., 2021). However, a number of studies have explored the relationship between university researchers' engagement and other factors such as gender, discipline, and satisfaction; the literature still needs more insights.

In the following, we explore the most important costs of university-industry research collaboration in more detail.

The lack of necessary resources to monitor activities between universities and industry: Collaborative research projects have specific conditions compared to other types of projects, such as construction projects. A major difference is in the goal-setting process, which is highly dynamic and emergent in the R&D context (Fernandes et al., 2021). Besides, most of the research projects that are conducted under collaboration between universities and industries have some significant characteristics that make them particular. These characteristics include: "involving different cultural traditions", "having a mix of industry and academia", "having a high complexity and uncertainty", and "handling multidisciplinary projects" (Fernandes et al., 2021). All of these characteristics make monitoring of activities between university and industry more crucial for the success of the projects. Meanwhile, universities also suffer from a lack of different resources, such as infrastructural, financial, and human resources (Manzini et al., 2017). The literature proposes that university-industry collaboration management mechanisms (Huang & Chen, 2017) and using novel project management tools (Fernandes et al., 2020) can help universities monitor activities between university and industry.

Delving deeper into this issue, we should note that universities need to consider different financial, human, technological, and physical resources to monitor activities between universities and industry. They also need to focus on developing connected and online monitoring systems instead of traditional systems, which are mainly detached and offline (Kaiser et al., 2019). Developing and implementing modern monitoring systems has recently become increasingly important, particularly amid the Covid-19 Pandemic (Müller & Klein, 2020). Finally, it should be mentioned that monitoring systems are highly related to other systems such as planning, reservoir, human resources, and operational systems, making the development of these systems a complicated and impressive agenda (Kerzner, 2017). Based on our findings, the lack of necessary resources to monitor activities is one of the main costs of university-industry research collaboration, and the literature also has paid specific attention to this matter; however, there are a variety of issues to consider for further research.

Conflict of interest (different missions): A conflict of interest is a situation in which multiple interests, commitments, duties, missions, or goals, are associated with more than a particular role or practice (Davis & Stark, 2001; Komesaroff et al., 2019). Such a situation is serious since it can reduce the integrity and reliability of the decision-making process (Davis & Stark, 2001). The relationship between universities and industry is described in the literature as challenging, as the mission of the former has been shaped around teaching and research, and the mission of the latter has been shaped around economic development (Tavares et al., 2020). This challenge has compelled universities to expand their mission to contribute more to social and economic development (Pinheiro et al., 2015). Accordingly, many universities around the world have reformed their mission and developed entrepreneurial universities with enormous potential for innovation and economic development (Guerrero et al., 2015).

Although the key element of the engagement between universities and companies is knowledge (Chiang, 2011), they both have different knowledge dispositions. While universities are concerned with knowledge dissemination, publishing, discovery, openness, sharing, and basic and upstream research, industrial firms are mainly focused on profitability, protecting commercial interests, preserving competitiveness in the market, and applied and downstream research (Tavares et al., 2020). Some studies in the literature have highlighted the conflict of interest as a prominent cost of university-industry collaboration (e.g., (Crespo & Dridi, 2007) and (Azman et al., 2019)) and their attitude is aligned with our findings. Managing conflict of interest is strongly associated with the success of research collaboration, and universities need to invest in their capabilities and capacities to handle conflicts of interest. It can happen in several ways, including training, establishing different well-matched processes, thinking about the interests of other parts, declaring and talking about the interests, and using mediators (Curzer & Santillanes, 2012; Elliott, 2014).

Several studies have addressed financial, operational, and logical issues associated with the conflicts between attitudes and cultures of universities and industries. However, the future literature needs to deepen the understanding of the changing nature of university-industry research collaboration and discuss the challenge from different stakeholders' perspectives (Tavares et al., 2020)

Increased resistance to change among employees: Given the necessity for change in both educational and industrial environments, it is not surprising that resistance to change has become an issue of special importance to decision-makers and researchers (Amarantou et al., 2018). Educational institutions like universities generally convey well-established traditions and a deeply rooted culture, which heavily resist change efforts (Palumbo & Manna, 2019). University-industry research collaboration requires universities to contribute continuous improvement practices to changing conditions to achieve effectiveness (Mortara et al., 2010). Resistance is rooted in fear of the unknown (Robinson & Goodey, 2018), and universities must help their researchers to conquer their fear of collaborating with industry.

There are several ways that universities can try to deal with resistance to change. For example, they can effectively engage professors and researchers, implement change in several stages of collaboration with industry, and communicate change effectively (Bjursell & Engström, 2019; Sammut, 2020). Resistance to change can be found at three levels: organizational, group, and individual. In the case of university-industry research collaboration, investigating the phenomenon of resistance to change at all three levels can be insightful since there is still relatively limited knowledge concerning the factors that trigger this behavior at universities (Amarantou et al., 2018).

An increased employees' tendency to avoid using the knowledge that they do not create themselves: The not-invented-here (NIH) syndrome is about having a negative attitude toward knowledge originating from a source outside the institution (Lichtenthaler & Ernst, 2006). Because of this prejudice, external technologies and knowledge may be evaluated wrongly, or their implementation may fail (Grosse Kathoefer & Leker, 2012). NIH syndrome also affects the complete knowledge cycle between universities and industrial firms, leading to severe disturbances in knowledge transfer (Grosse Kathoefer & Leker, 2012). It has been disclosed that developing an innovation climate and establishing programs or workshops in entrepreneurship encourage positive interactions among partners and mitigate the NIH syndrome (Tseng et al., 2020).

NIH syndrome happens because university researchers think there is no reward for integrating external ideas and believe that external ideas, particularly those from industry, are inferior. In this regard, universities can encourage searching for knowledge external to the university and also reward using and developing external knowledge and ideas (Antons & Piller, 2015; Myers et al., 2019). Although NIH syndrome is cited as one of the main costs in the transfer of external knowledge, scientific evidence on ways to overcome NIH syndrome remains scarce (Antons et al., 2017). In addition, this phenomenon has been mainly analyzed in an industrial context (Grosse Kathoefer & Leker, 2012), and it is recommended for future researchers to analyze this phenomenon in an educational context.

Paying time costs associated with bureaucracy rules: Although some experts believe that bureaucracy is the indispensable outcome of complex businesses operating in complicated regulatory and international environments, there are new realities supporting the idea that bureaucracy is avoidable and reluctant (Hamel & Zanini, 2018). For instance: competitive advantage comes from innovation, not sheer size; today's employees are skilled, not uneducated; the pace of change is hypersonic, not slow; and communication is instantaneous, not convoluted (Hamel & Zanini, 2018). In university-industry research collaboration, bureaucracy is highlighted, and a substantial issue in implementing knowledge transfer mechanisms is the bureaucracy and inflexibility of universities and industrial firms (Alexander et al., 2020).

Although the first definitive emergence of bureaucracy occurred in civilizations, it has been revolutionized in different eras. In particular, facing the COVID-19 pandemic, firms around the world implemented and developed digital bureaucracy, which is a new concept in the field of governance (Abdou, 2021). Universities also need to pay attention to the costs related to bureaucracy, especially its modern forms, when it comes to university-industry research collaboration. Even though dealing with bureaucracy is challenging, universities can handle it by eliminating paperwork, cutting out processes, empowering people, and facilitating the flow of information (Bozeman & Youtie, 2020). In addition, future researchers and managers should be mindful of not radically increasing the number of rules to try to solve the problems related to the institution's growth since this leads to more bureaucracy and paying more time costs (Alexander et al., 2020).

Loss of focus: Academic freedom is considered a crucial issue in the university environment, and loss of it results in loss of focus (Behrens & Gray, 2001; Helm et al., 2019). Some works in the literature emphasize that researchers are concerned about the impact of close university-industry collaboration, which is perceived to interfere with their academic freedom (Lee, 1996; Tartari & Breschi, 2012). Also, the fear of loss of freedom and control over research projects has a significant negative impact on the degree of collaboration between universities and industries (Azagra-Caro et al., 2006). In general, scientists need to have control over projects to undertake and what methods to use to tackle them. Their willingness to participate in collaboration affects the success or failure of university-industry collaboration (Davis et al., 2011).

It should also be mentioned that the academic freedom of professors must be viewed distinctly from institutional freedom (Fossey, 2007). Also, the issue of academic freedom must be explored while legal frameworks (Neil, 2018) and ethical issues (Rajagopal, 2003) have taken into account. Although our findings show that the loss of focus is one of the most important costs of university-industry research collaboration, only a few studies explicitly address the consequences of cooperative research and their impact on the loss of freedom and focus (Tartari & Breschi, 2012). In this regard, it is recommended for future researchers to deeply analyze the problem of loss of focus in the context of university-industry research collaboration.

8. Research application

This research will help researchers fundamentally explore and compare the potential benefits and the potential costs of open innovation for universities regarding their research collaboration with industries. It will enable researchers to analyze open innovation's related issues for universities more effectively and define their collaborative research projects on these issues in line with the priorities of universities.

Furthermore, the research's findings will make universities capable of predicting and managing the uncertainties arising from open innovation for universities since they will be aware of different clusters of costs and their detailed characteristics in terms of performance. Meanwhile, they can also make informed decisions about the open innovation projects because of their information on the nature and degree of benefits and costs of open innovation for universities.

Concerning the most important benefits of collaboration with industry proposed in this study, universities can focus on the most rewarding aspects of research-industry collaboration and develop their strategies and agendas around them. They also can find the most critical costs of collaboration with industry and handle them expeditiously. In the discussion section, we presented the nature of the benefits and costs and maintained how universities could profit from the collaboration with industry in different ways.

For instance, the study's findings suggest that universities need to emphasize sharing specialized infrastructures to obtain operational and tactical flexibility and respond to emerging needs. They also should use different knowledge management mechanisms, including formal and informal, to achieve the most out of collaboration with the industry. Moreover, they need to establish and empower technology transfer offices to facilitate the process of technology transfer between academia and industry. Also, universities should encourage teamwork to get the most out of collaboration with the industry. In addition, the findings of this study show that implementing the learnings is one of the most important benefits of university-industry research collaboration, and universities need to invest in this benefit exclusively.

This study also explained how universities could effectively deal with the crucial costs of university-industry collaboration. For example, based on the study's findings, the lack of necessary resources to monitor activities is one of the main costs of university-industry research collaboration. So, universities need to invest in developing connected and online monitoring systems instead of traditional systems, which are mainly detached and offline. This study also emphasizes that conflict of interest is a crucial cost and promotes universities to establish different well-matched processes, think about the interests of other parts, declare and talk about the interests, and use mediators to manage conflict of interest. Also, the findings suggest that universities should implement change in several stages of collaboration with industry and communicate change effectively. In addition, universities need to handle bureaucracy-related problems by eliminating paperwork, cutting out processes, empowering people, and facilitating the flow of information.

In general, the results of this research can help both practitioners and researchers to have a clearer understanding of the benefits and costs of open innovation for organizations such as universities, colleges, teacher-training schools, research centers, institutes of technology, and professional schools providing preparation in specific fields as medicine, business, and art. Based on the findings of this research, these organizations can develop an appropriate framework and guidelines for research-industry collaboration.

Industrial firms can also use the study's findings to promote university-industry research collaboration at a large scale by targeting relevant motivations of universities. They learn what universities expect from a university-industry partnership and do marketing around to persuade universities to engage in collaborative research collaborations. They also understand the costs for universities and find remedies for them, encouraging universities to engage in university-industry collaboration. In general, this could equip industrial firms to make relevant strategies to target universities.

9. Conclusions, Limitations, and Future Research

In innovation management, open innovation has become one of the topical issues attracting increasing scholarly attention. Open innovation promotes the usage of the input of outsiders to strengthen internal innovation processes and the search for outside commercialization opportunities for what is developed internally. Open innovation has enabled both academics and practitioners to design innovation strategies based on the reality of our interconnected world. Practicing open innovation has many benefits, including, for example, increased revenue, increased know-how, improved brand reputation, reduced R&D Costs, and improved long-term profitability. In addition, open innovation is also associated with different costs, including, for example, the reduced rarity of knowledge assets, increased possibility of knowledge leakage, loss of focus, and lack of the necessary resources to monitor activities.

Although some studies have identified and explored a variety of the benefits and costs of open innovation in terms of their importance to firm performance, they suffer from a significant shortcoming. Performance is a multidimensional concept and, therefore, must be evaluated from different dimensions, including financial, customer, business processes, and learning and growth. To the best of our knowledge, none of the studies in the literature allows scholars to compare the benefits and costs of open innovation in terms of different dimensions of performance. In this research, to analyze the benefits and costs of open innovation from different performance dimensions, we used a stochastic multi-criteria clustering method in which the benefits and costs were alternatives, and the different aspects of performance were criteria. Since there was no comprehensive understanding of the nature of the benefits and costs of open innovation, the proposed model aimed to cluster them into hierarchical groups in order to help researchers identify the most crucial benefits and costs in relation to different dimensions of performance. In addition, the model was able to deal with uncertainties related to technical parameters such as the criteria weights and preference thresholds.

We applied the model in the context of open innovation for universities concerning their research collaboration with industries. An online survey was conducted to collect experts' opinions on the open-innovation benefits and costs of university-industry research collaboration in view of different dimensions of performance. The results obtained through the cluster analysis specified that university researchers collaborate with industry mainly because of knowledge-related and research-related reasons rather than economic reasons. The results also indicated that the most important benefits of university-industry research collaboration for universities are implementing the learnings, increased know-how, accessing specialized infrastructures, accessing a greater idea and knowledge base, sensing and seizing new technological trends, and keeping the employees engaged. In addition, the results show that the most important costs are the lack of necessary resources to monitor activities between university and industry, an increased resistance to change among employees, conflict of interest (different missions), an increased employees' tendency to avoid using the knowledge that they do not create themselves, paying time costs associated with bureaucracy rules, and loss of focus.

The findings of this study help researchers fundamentally cluster, explore and compare the potential benefits and the potential costs of open innovation for universities regarding their research collaboration with industries. They also enable researchers to analyze issues related to open innovation for universities more effectively and to define their research projects on these issues in line with the priorities of universities. Meanwhile, the researchers can also make informed decisions about the open innovation projects using their information about the nature and degree of the benefits and costs of open innovation for universities. Finally, the results of this research can help both practitioners and researchers to have a clearer understanding of the benefits and costs of open innovation for organizations such as universities, colleges, teacher-training schools, research centers, institutes of technology, and professional schools providing preparation in specific fields such as medicine, business, and art. Based on the findings of this research, these organizations can develop an appropriate framework and guidelines for research-industry collaboration.

This study has expanded knowledge about university-industry research collaboration, but it also has some limitations that call for future research. Our research explored the benefits and costs of university-industry research collaboration from the viewpoint of universities; however, the benefits and costs should also be explored from the views of industries and governments. Also, universities can collaborate with industries in different ways, such as through research, teaching, workshops, and internship programs. This study focused on research collaboration, although future studies can focus on many other types of collaboration between universities and industries. Also, we addressed the benefits and costs of university-industry collaboration, while future researchers can address other concepts such as drivers and barriers. Lastly, this study was developed based on the opinions of the faculties of the University of Ottawa, while the opinions of other expert communities need to be considered in future studies. Despite these limitations, we believe that our study provides empirical insights that were previously lacking in the literature on open innovation, particularly in the context of university-industry research collaboration. Our results add to the understanding of what areas universities must pay more attention to when it comes to university-industry research collaboration.

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Appendix 1

Table A1 Related questions concerning clustering benefits

Label	Benefit	Related question	Values
Be01	Implementing the learnings	In university-industry research collaboration, university researchers can implement their learning. Which of the following items will be improved highly (or very highly) if university researchers implement their learning in industrial research projects?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be02	Increased know-how	Collaboration between universities and industries increases the know-how of university researchers. Which of the following items will be improved highly (or very highly) by the Increased know-how of university researchers?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be03	Accessing specialized infrastructures	Collaboration between universities and industries helps universities to access specialized infrastructures for research such as laboratories, data, and technologies. Which of the following items will be improved highly (or very highly) by access to technological infrastructures?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be04	Reduced R&D Costs	Collaboration between universities and industries helps universities to reduce their R&D costs. Which of the following items will be improved highly (or very highly) by reducing R&D Costs of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be05	Improved teamwork and collaboration abilities	In university-industry research collaboration, teamwork and collaboration abilities will be improved. Which of the following items will be improved highly (or very highly) by university members' improved teamwork and collaboration abilities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be06	Accessing a greater idea and knowledge base	Collaboration between universities and industries helps universities to access greater ideas and knowledge base. Which of the following items will be improved highly (or very highly) if universities access the greater ideas and knowledge base?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)

Be07	Being more productive in terms of publication	Research collaboration can make universities more productive in terms of publication. Which of the following items will be highly (or very highly) improved by being more productive in terms of publication?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be08	Gathering information for teaching	Universities can gather information for better teaching via collaboration with industry. Which of the following items will be improved highly (or very highly) by improving teaching in universities via gathering industry information?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be09	Accessing talent	Collaboration between universities and industries helps universities to access talents. Which of the following items will be improved highly (or very highly) by providing opportunities for universities to access talents?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be10	Sharing risks of projects	Universities can share risks of research projects via collaboration with industry. Which of the following items will be improved highly (or very highly) by sharing risks of research projects?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be11	Discovering market needs	In university-industry research collaboration, the university can discover market needs better. Which of the following items will be improved highly (or very highly) when universities get able to discover market needs?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be12	Improved brand reputation	Collaboration between universities and industries helps universities to improve their brand reputation. Which of the following items will be improved highly (or very highly) by improving universities' brand reputation?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be13	Increased commercialization capacity	Collaboration between universities and industries helps universities to increase their commercialization capacity. Which of the following items will be improved highly (or very highly) by the increased commercialization capacity of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)

Be14	Sensing and seizing new technological trends	Collaboration between universities and industries helps universities sense and seize new technological trends. Which of the following items will be improved highly (or very highly) through sensing and seizing new technological trends by universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be15	Creating new revenue streams from NPD	University-industry research collaboration helps universities create new revenue streams from new product development (NPD). Which of the following items will be improved highly (or very highly) by creating new revenue streams for universities from NPDs?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be16	Learning from other organizational cultures and their management systems	Collaboration between university and industry helps the university learn from other organizational cultures and management systems. Which of the following items will be improved highly (or very highly) if universities learn from other organizational cultures and management systems?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be17	Increased patents	Universities can increase their patents via collaboration with industry. Which of the following items will be improved highly (or very highly) by the increased number of patents?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be18	Keeping the employees engaged	University-industry research collaboration can keep academic persons more engaged. Which of the following items will be improved highly (or very highly) by keeping the academic persons more engaged in research activities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Be19	Increased agility	Universities can be more agile via collaborating with industry. Which of the following items will be improved highly (or very highly) by the increased agility of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)

Table A2 Related questions concerning clustering costs

Label	Cost	Related question	Values
Co01	Lack of the necessary resources to monitor activities between university and industry	Lack of the necessary resources of universities to monitor activities between university and industry can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co02	Facing different cultures and terminologies	Universities and industries have different cultures and terminologies. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co03	Increased resistance to change among employees	In university-industry research collaboration, there is a possibility of resistance to change among partners. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co04	Difficulty to coordinate the activities between university and industry	Difficulty to coordinate the activities between university and industry can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co05	Increased possibility of the knowledge leakage	In university-industry research collaboration, there is a possibility of knowledge leakage. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co06	limiting or causing delays in the publication of scientific articles	In university-industry research collaboration, firms can limit or cause delays in the publication of scientific articles. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co07	Increased costs to absorb external knowledge	Collaboration between universities and industries makes universities spend money to absorb external knowledge. This cost can adversely affect highly (or very highly) which	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No)

Label	Cost	Related question	Values
		of the following aspects of universities?	□ University financial resources such as funds and capital assets (Yes/No)
Co08	Conflict of interest (different missions)	University and industry have different missions and interests. This conflict of interest can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co09	Increased employees' resilience due to NIH syndrome (tendency to avoid using the knowledge that organizations do not create themselves)	In university-industry research collaboration, there is a possibility of NIH syndrome (tendency to avoid using the knowledge that universities/organizations do not create themselves). It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co10	Reduced rarity of knowledge assets	Collaboration between universities and industries can reduce the rarity of knowledge assets. Which of the following aspects of universities will be affected highly (or very highly) by the reduced rarity of knowledge assets?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co11	Paying time costs associated with bureaucracy rules	Research collaboration between universities and industries makes universities pay time costs associated with bureaucracy rules. This cost can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co12	Paying extra costs of relationship maintenance	Research collaboration between universities and industries makes universities pay extra costs of relationship maintenance. This cost can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)
Co13	loss of focus	In university-industry research collaboration, universities may lose their focus on their main research fields. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)

Label	Cost	Related question	Values
Co14	spending time scouting potential partners	In university-industry research collaboration, universities need to spend time exploring and investigating enterprise ventures. It can adversely affect highly (or very highly) which of the following aspects of universities?	□ Skills and knowledge of faculty members (Yes/No) □ University research excellence (Yes/No) □ University reputation (Yes/No) □ University financial resources such as funds and capital assets (Yes/No)

Appendix 2

Codes:

```
General (Monte Carlo Simulation) (R)

dataset2=Datapre2 (dataset2)

totalobjects=matrix("start", nrow = 1, ncol = 14)

 e=0.5

 ty="Co"

 assign(paste("totalobjects",ty,e,sep=""),totalobjects)

for (h in 1:10000) {

 for(i in 1:100 )

 {for (j in 1:2)

 {assign(paste("objects",j,"yyyy",i,sep=""),NULL)

 }}

 PRUPDATE3 (dataset2)

 Matrix=assign(paste("y",ty,e,"s",h,sep=""), lastmat1)

 get(paste("y",ty,e,"s",h,sep=""))

 Clusteringyyyy1(lastmat1,e)

 for(i in 1:100 )

{for (j in 1:2)

{totalobjects=rbind(totalobjects,get(paste("objects",j,"yyyy",i,sep="")))}


 totalobjects=rbind(totalobjects,"separator")

 }
```

```
assign(paste("totalobjects",ty,e,sep=""),totalobjects)
```

The PROMETHEE (R)

```
PRUPDATE3()

function(dataset2) {
 k=ncol(dataset2)
 n=nrow(dataset2)
 nc= nrow(dataset2)
 datasetk=matrix(, nrow = n^2, ncol = k)
 for(p in 1:n){
 for(j in 1:k){
 for(i in 1:n){
 datasetk[i+(p-1)*nc,j]=dataset2[i,j]}}}
 datasetk2=matrix(, nrow = n^2, ncol = k)
 for(p in 1:n){
 for(j in 1:k){
 for(i in 1:n){
 datasetk2[i+(p-1)*nc,j]=dataset2[p,j]}}}
 datasett=datasetk2-datasetk
 datasett2=datasett
 y=ncol(datasett)
 x=nrow(datasett)
  for (j in 1:y){
 for (i in 1:x){
 if (datasett [i,j]<0)
```

```
{datasett2 [i,j]=0}
else if (datasett [i,j]>=0){datasett2[i,j]= datasett [i,j]
}}}
we= datasett
for (j in 1:y)
{we[1,j]= runif(1)}
for (j in 1:y) {
for (i in 2:x)
{we[i,j]= we[1,j]}}
wesum= matrix(0, nrow = x, ncol = 1)
for (e in 1:y) {
for (a in 1:x)
{wesum[a, 1]= wesum[a, 1]+ we[a,e]}}
datasetcol= matrix(0, nrow = x, ncol = 1)
for (i in 1:x) {
for(j in 1:y)
{datasetcol[i,1]=(we[i,j]/ wesum[i, 1])*datasett2[i,j]+datasetcol[i,1]}}
lastmat= matrix(0, nrow = nc, ncol = nc)
row.names(lastmat) <- 1 : nc
for(i in 1:nc) {
for(j in 1:nc) {
lastmat[i,j]=datasetcol[j+(i-1)*nc,1]
}}
```

```
lastmat1<<-lastmat

View(lastmat1)

}
```

Stochastic Clustering Code (R):

```
function (lastmat1, e)

{

 matclustayyyy1 = lastmat1

 matclusta1yyyy1 = matclustayyyy1

 matclusta2yyyy1 = matclustayyyy1

 mata1yyyy1 = matclustayyyy1

 mata2yyyy1 = matclustayyyy1

 cyyyy1 = ncol(matclustayyyy1)

 ryyyy1 = nrow(matclustayyyy1)

 which(matclustayyyy1 == max(matclustayyyy1))

 aayyyy1 = which(matclustayyyy1 == max(matclustayyyy1), arr.ind = TRUE)

 matclustnuma1yyyy1 = aayyyy1[1]

 matclustnuma2yyyy1 = aayyyy1[2]

 matclustdivayyyy1 = matrix(0, nrow = 3, ncol = ryyyy1)

 for (i in 1:ryyyy1) {

 matclustdivayyyy1[1, i] = max(matclustayyyy1[i, matclustnuma1yyyy1],

 matclustayyyy1[matclustnuma1yyyy1, i])

 }

 for (i in 1:ryyyy1) {

 matclustdivayyyy1[1, i] = max(matclustayyyy1[i, matclustnuma1yyyy1],

 matclustayyyy1[matclustnuma1yyyy1, i])

 matclustdivayyyy1[2, i] = max(matclustayyyy1[i, matclustnuma2yyyy1],
```

```
matclustayyyy1[matclustnuma2yyyy1, i])
}
matclustdivayyyy1[3, ] = matclustdivayyyy1[2, ] - matclustdivayyyy1[1,
]
dataset2numa1yyyy1 = character()
dataset2numa2yyyy1 = character()
for (i in 1:cyyyy1) {
if (matclustdivayyyy1[3, i] > 0) {
dataset2numa1yyyy1 = c(dataset2numa1yyyy1, i)
}
else {
dataset2numa2yyyy1 = c(dataset2numa2yyyy1, i)
}
}
for (i in 1:cyyyy1) {
uyyyy1 = cyyyy1 - i + 1
if (matclustdivayyyy1[3, uyyyy1] > 0) {
mata2yyyy1 = mata2yyyy1[-uyyyy1, -uyyyy1]
}
else {
mata1yyyy1 = mata1yyyy1[-uyyyy1, -uyyyy1]
}
}
```

```
mata2yyyy1 = as.matrix(mata2yyyy1)

mata1yyyy1 = as.matrix(mata1yyyy1)

rownames1yyyy1 = rownames(mata1yyyy1)

rownames2yyyy1 = rownames(mata2yyyy1)

mata1nullyyyy1 = mata1yyyy1

diag(mata1nullyyyy1) <- NA

da1yyyy1 = max(mata1yyyy1) - min(mata1nullyyyy1, na.rm = TRUE)

mata2nullyyyy1 = mata2yyyy1

diag(mata2nullyyyy1) <- NA

da2yyyy1 = max(mata2yyyy1) - min(mata2nullyyyy1, na.rm = TRUE)

objects1yyyy1 = NULL

objects2yyyy1 = NULL

(if (da1yyyy1 <= e) {

objects1yyyy1 = rownames1yyyy1

objects1yyyy1 <<- objects1yyyy1

})

(if (da2yyyy1 <= e) {

objects2yyyy1 = rownames2yyyy1

objects2yyyy1 <<- objects2yyyy1

})

(if (da1yyyy1 > e) {

Clusteringyyyy2(mata1yyyy1, e)

})
```

```
(if (da2yyyy1 > e) {

Clusteringyyyy3(mata2yyyy1, e)

})

}
```

Cluster Ensembling Code (MATLAB)

```
function clusterid=HBGF_spec(ceresults, idxs, k)

sresults = ceresults(:, idxs);

esize = length(idxs);

instnum = size(ceresults,1);

w=formw(sresults, esize, instnum);

csize=sum(w);

w = w*diag(1./sqrt(csize));

 [u,s,v]= svds(w,k);

u = u./repmat(sqrt(sum(u.^2,2)), 1, k);

v = v./repmat(sqrt(sum(v.^2,2)), 1, k);

idxperm=randperm(instnum);

centers(1,:) = u(idxperm(1),:);

c=zeros(instnum,1);

c(idxperm(1),1) = 2*k;

for i=2:k

 c=c+abs(u*(centers(i-1,:))');

 [y,m] = min(c);

 centers(i,:) = u(m, :);

 c(m,1) = 2*k;

  end

clusterid= kmeans(vertcat(u,v), k, 'start', centers, 'maxiter', 200, 'emptyaction', 'singleton');

clusterid(instnum+1:size(clusterid,1), :) = [];
```

```
function w=formw(idxs, r, instnum)

site=1;

for i=1:r

 idx = idxs(:,i);

 uniqueks=unique(idx(idx>0));

 t=zeros(instnum, length(uniqueks));

 t(find(repmat(idx, 1, length(uniqueks)) == repmat(uniqueks', instnum, 1)))=1;

 w(:, site:site+length(uniqueks)-1) = t;

 site=site+length(uniqueks);

end
```