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Systematizing serendipity for big science infrastructures: The ATTRACT project

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ABSTRACT

Big Science Research Infrastructures (BSRIs) are tremendous sources of 'deep-tech' with the potential to foment alternative commercial applications in diverse industries. Yet, cultivating novel applications of BSRI technologies is not straightforward due to misalignment between their scientific mission, large technological risks, market uncertainties, and long development times. Given these challenges, research is needed to understand if- and how- serendipitous innovations can be purposefully developed from BSRIs. In this study, we analyse ATTRACT, a novel initiative funded by the European Commission's Horizon 2020 program, which funded 170 projects with €100,000 each to develop a proof-of-concept commercial application of BSRI technologies within one year. Our analysis of this dataset identifies three modes employed by researchers to come up with alternate applications: (1) combining different technologies, (2) applying technology into a different field, and (3) using artificial intelligence or machine learning. In a second step, we conducted multinomial logistic regressions using the project data, expert evaluations, and a questionnaire to identify the antecedents associated with the pursuit of each of the three modes. Our findings suggest that scientists and engineers develop many new ideas about novel potential applications of BSRI technologies in their daily work. The main value of ATTRACT is in facilitating project development through financial resources, brokering relationships with industrial partners, and facilitating the applications of technologies in domains outside of the immediate purview of BSRIs.

1. Introduction

Some of the most pervasive technologies in society today such as the World Wide Web, touchscreens, and radiotherapy result from leveraging research generated by Big Science Research Infrastructures (BSRIs) in areas beyond their original scientific purview. While it is long known that BSRIs are fertile ground for many promising innovations (Mazzucato, 2013; Scarrà and Piccaluga, 2020), it is still unclear how these BSRIs can be purposefully cultivated to find alternate applications for the technologies already developed within these organizations. In parallel, scholars have recently sought to identify how technologies find alternate applications outside of their original intended use under the theme of serendipity (Andriani and Kaminska, 2021; Garud et al., 2018; Yaqub, 2018). At the intersection of these two themes, this study explores an initiative that aims to systematize the serendipitous exploration of technologies from BSRIs for alternative commercial applications.

The serendipity literature has recently seen the emergence of systematic analyses that offer a more nuanced understanding of its antecedents and mechanisms (e.g. Garud et al., 2018; Yaqub, 2018). Instead of seeing serendipity as pure luck, recent theoretical developments emphasize the deliberate effort required in its pursuit (de Rond, 2014). However, while there has been much conceptual development on serendipity, empirical evidence is still lacking on its antecedents and modes.

Given their track record of finding successful alternate applications for the various instruments they operate, BSRIs provide a rich context to understand serendipity (Mazzucato, 2013; Scarrà and Piccaluga, 2020). If we can delineate the formative conditions of serendipity specific to BSRIs, this can, in turn, guide the design of mechanisms to realize the

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peripheral benefits of scientific research infrastructures. However, big science is fundamentally different from other innovation contexts (Autio, 2014; Florio and Sirtori, 2016; Hallonsten, 2020; Scarrà and Piccaluga, 2020). Their cultures are often antagonistic to commercialization (Puliga et al., 2020); their scientific programs span decades and are out of synch with shorter horizons of venture capital (Anderson et al., 2012); their technologies are characterized as 'deep tech', which refer to early-stage, enabling technologies encompassing fundamental functions such as sensing, imaging, detection, connectivity, computation, inference, actuation, and control across both hardware and software (Siegel and Krishnan, 2020). As early-stage technologies, deep technologies are distant to immediate market applications and often require substantially more development compared with consumer-facing products (Byckling et al., 2000; Vuola and Hameri, 2006).

With their extremely high investment levels, research infrastructures are normally funded by taxpayers via national ministries or funding agencies – often in pan-national consortia (Hallonsten, 2020; Williams and Mauduit, 2020). As such, it bears upon policymakers to seek mechanisms to optimize the potential socioeconomic value of these significant public investments (Florio et al., 2016; Scaringella and Chanaron, 2016). Beyond technology transfer offices, purposeful, forward-looking mechanisms to realize these outcomes are under-researched and thus, warrant additional attention.

In this study, we analyse the ATTRACT[1] project, a €20 M initiative funded within the Horizon 2020 Framework Programme of the European Commission that aims to systematize the discovery of breakthrough applications of imaging, detection, computational, and other deep technologies from the leading European science research infrastructures. ATTRACT supported 170 projects with the seed-funding of €100,000 each to leverage BSRI technologies towards creating sustainable businesses. Leveraging this data, the overarching research question of this study is to understand how researchers from BSRIs find alternate uses of their technologies and how initiatives like ATTRACT enable these different modes.

In the first phase of analysis, we use data from the 170 project proposals to identify the modes pursued by researchers within these BSRIs. These are: (1) combining different technologies; (2) applying from one field to another; and (3) using artificial intelligence (AI) or machine learning (ML) – processes which have been described in the innovation literature at large, yet not related in studies of serendipity. In the second phase, we performed multinomial logistic regression using the project data, expert evaluations, and a questionnaire to identify the antecedents; that is, factors correlated with the pursuit of each mode.

This article proceeds by reviewing the literature on serendipity. We then turn to big science to understand its historical role in generating novel innovations from its research technologies and the rationale from which policymakers seek applications of science towards social and economic impact. We then present the ATTRACT project and analyse how it attempts to systematize serendipity. Our findings examine how serendipity emerging in BSRIs compares with concepts in the extant serendipity literature and presents evidence on the determinants and antecedent conditions by which serendipity can be cultivated. We conclude with observations concerning future policy initiatives concerning big science, innovation, and socioeconomic value.

[1] ATTRACT members include: the European Organization for Nuclear Research (CERN), European Molecular Biology Laboratory (EMBL), European Southern Observatory (ESO), European Synchrotron, Radiation Facility (ESRF), European X-Ray Free-Electron Laser Facility (European XFEL), and the Institut Laue-Langevin (ILL), Aalto University, ESADE Business School, and the European Industrial Research Management Association (EIRMA).

2. Theory

Understanding how technologies find applications outside of their original intended use has gained much attention from innovation scholars in recent years (Andriani and Kaminska, 2021; Garud et al., 2018; Yaqub, 2018). Underpinning this phenomenon is the concept of serendipity which refers to the unanticipated discovery of something beneficial.

2.1. Serendipity and its modes

The term serendipity was coined by writer Horace Walpole in 1754 inspired by the Persian fairy tale, *Three Princes of Serendip* (Cunha et al., 2010; Rosenman, 2001). He refers to serendipity as an unexpected discovery found from the combination of accident and sagacity (Rosenman, 2001). Sagacity refers to having perception and sound judgment, or in other words, a prepared mind. As such, instead of being merely interchangeable with the words luck, happenstance or providence, serendipity is better seen as a capability requiring the focus of attention (de Rond, 2014). An equivalent formulation can be seen in the context of entrepreneurship as the combination of directed search, favourable accidents, and prior knowledge (Dew, 2009). By stripping away the random and sometimes mystical aspects of serendipity, it becomes a concept that can be subject to a more rigorous evaluation of its triggers, antecedents, and mechanisms. We summarize various definitions of serendipity in Table 1.

The salient tension in the serendipity discourse between something purely accidental or purposefully sought is manifest in many nuanced characterizations that synthesize these absolute modes. An emphasis on purposeful seeking is considered by de Rond (2014) who classifies serendipity according to a) whether the solution was the intended target, and b) whether the original research design was causal to the solution. Hence, the term *pseudo-serendipity* is evoked by de Rond (2014)

Table 1
Serendipity definitions (adapted and extended from Grange et al. (2019)).

Definition of serendipity	Context	Source
An incident-based, unexpected discovery of information when the actor is either in a passive, nonpurposive state or an active, purposive state, followed by a period of incubation leading to insight and value	Information	Agarwal (2015)
"The fairly common experience of observing an unanticipated, anomalous and strategic datum which becomes the occasion for developing a new theory or for extending an existing theory"	Science and Technology	Merton (1948 p. 506)
The art of making an unsought finding, where a finding is something "new and true (science), new and useful (technology), or new and fascinating (art)"	Science and Technology	Andel (1994)
The accidental discovery of something valuable	Organizational learning	Cunha et al. (2010)
"The process of identifying meaningful pairings of two or more observations, events or fragments of information that can be put to practical or strategic use"	Innovation	de Rond (2014)
The finding of things without seeking them	Creativity	Austin (2003)
Search leading to unintended discovery It is a combination of search, contingency, and prior knowledge	Entrepreneurship	Dew (2009)
In recommendation systems, serendipitous items are relevant, novel, and unexpected for a particular user. Serendipitous items are unpopular and significantly different from the user profile	Recommendation systems	Kotkov et al. (2016)

to describe when the solutions are intended in the first place, compared to (just) serendipity where the solutions are completely unanticipated or accidental. Alternatively, Garud et al. (2018) employ concepts from evolutionary biology to introduce the term “exaptation” to refer to the “emergence of functionalities for scientific discoveries that were unanticipated ex-ante” (pp.126). They identify two forms of exaptation: (1) *franklins* and (2) *miltons*. *Franklins* refer to the supplementary usage of an existing structure in areas they were not originally intended for (e.g. using coins as screwdrivers). *Miltons* refer to discoveries without a currently known function. A widely known image to illustrate miltons is that of spandrels, the triangular space unintendedly created by the shape of arches, which were later used as a blank canvas for painting (Gould, 1997).

Perhaps the most well-known attempt to understand serendipity methodically was initiated by Robert Merton in the 1950s, with a dedicated book in 2004 (Merton and Barber, 2004). Yaqub (2018) conducted a systematic review of Merton’s archives to identify four specific archetypes of serendipity, which he organizes according to whether: a) there is a targeted line of inquiry; and b) the type of solution discovered. According to these criteria, (1) *Walpolian* serendipity is defined where a targeted line of inquiry leads to discoveries that researchers were not in search of (i.e. solution to a different problem). (2) *Mertonian* serendipity happens where the desired solution is achieved via an unexpected route (i.e. targeted problem – different path). (3) *Bushian* serendipity is where untargeted exploratory research leads to a solution for a well-known problem. Finally, (4) *Stephanian* serendipity is where untargeted research finds an unsought solution, that may find a future application.

We present four distinct organizing typologies of serendipity in Table 2 below.

Table 2
Typologies of serendipity.

de Rond (2014)	Yaqub (2018)	Mirvahedi and Morrish (2017) Friedel (2001)	Garud et al. (2018)
Serendipity by way of random variation Serendipity as the unintended consequence of design	Walpolian Targeted search solves the unexpected problem	Galilean find something unsought due to sagacity Columbian Find something when you are looking for something else	Franklins the character was previously shaped for some users but is now coopted for a different role (ex. coin as a screwdriver)
Pseudo-serendipity by way of random variation Pseudo-serendipity as the unintended consequence of design	Mertonian Targeted search solves problem via an unexpected route	Archimedean looking for something, and they accidently find it	
	Bushian Untargeted search solves an immediate problem	Entrepreneurial look for any opportunity and explore an appropriate opportunity that comes along	
	Stephanian Untargeted search solves a problem later		Miltons the character was not shaped for some use but has the potential to be coopted for another use (ex. spandrels)

2.2. Serendipity antecedents

To a large degree, extant typologies of serendipity only characterize unexpected outcomes after they have occurred. These categorizations have not been as useful in informing the concrete actions to increase the likelihood of such unexpected outcomes. Hence, it is useful to consider research that delineates the antecedents that enable serendipity.

Scholars have started to catalog the different antecedents, that is conditions conducive to serendipity (Kato et al., 2019; Lane et al., 2019; Sauer and Bonelli, 2020). Garud et al. (2018) describe the organizational structures to induce exaptive serendipity that includes patent and publications databases (exaptive pools), technology fairs (exaptive events), and workshops (exaptive forum). Cunha et al. (2010) identify organizational attributes that facilitate serendipity including boundary spanning, mindfulness, social networks, teamwork, free space for creativity, and opportunities for playing with ideas.

McCay-Peet and Toms (2015) propose a process model to explain how individuals discover and perceive serendipitous events, which consists of: trigger, connection, follow-up, valuable outcome, and an unexpected thread. The trigger is the first step and refers to environmental cues sparking the interest of the individual. In a second phase, this trigger is connected by the individual to their previous knowledge and experiences. Afterward, individuals follow up on these triggers to obtain a valuable outcome. In the last step, the surprise occurs from noticing the unexpected thread present from the previous processes.

Makri et al. (2014) identify more actionable strategies towards serendipity including “varying their routines, being observant, making mental space, relaxing their boundaries, drawing on previous experiences, looking for patterns and seizing opportunities” (p. 2186). Yaqub (2018) echoes these themes, recommending: (1) examining deviations from theory, (2) activating previously acquired knowledge and experiences from individuals, (3) tolerating errors and following up on such occurrences, and (4) leveraging network.

Most recently, technology has received attention as a useful tool to foment serendipity. For example, in drug discovery, artificial intelligence has been used to repurpose drugs in new therapeutic areas (Mak and Pichika, 2019). The ability of computers to generate so many alternative scenarios and combinations enables artificial systems that “catalyze, evaluate and leverage serendipitous occurrences themselves" (Corneli et al., 2014 p.2). Austin et al. (2012) enumerate principles on how organizations can emulate computational systems towards accidental innovation by supporting outcome variation, offering induced variation, encouraging random retrieval and revisiting of collected knowledge, and supporting the modulation of iteration rates and convergence towards final outcomes.

2.3. Big science as an incubator for serendipity

BSRIs are defined by Florio and Sirtori (2016) as institutions with a) high capital intensity, b) long-lasting facilities or networks, c) operating in monopoly or oligopoly conditions affected by externalities, and d) who produce social benefits via the generation of new knowledge (either pure or applied). In Europe alone, there are at least 55 such research infrastructures spanning different fields such as energy, environment, health and food, physical sciences and engineering, social and cultural innovation, and digital (European Strategy Forum on Research Infrastructures (ESFRI), 2008). In the US, the National Science Foundation supports at least 130 research infrastructures including telescopes, observatories, aircraft, vessels, and cyberinfrastructures (National Science Foundation, 2011).

The model of big science was institutionalized by Ernest Orlando Lawrence at the University of California, Berkeley with the development of the cyclotron: a device for accelerating nuclear particles to very high velocities to bombard, disintegrate and form completely new elements and radioactive isotopes. While the first cyclotron was merely a simple 4-inch device that could be held in the human hand, over time, larger versions that could achieve greater energy levels were created. With each subsequent generation of the cyclotron, a greater number of physicists, engineers, and chemists were needed for construction, operation, and maintenance. Departing with the ideal of the lone genius in the laboratory of 'smaller science' (de Solla Price, 1963; Hiltzik, 2016), Lawrence and colleagues advanced a form of team-based, industrialized science that subsequently matured into large research teams with hundreds of scientists and engineers.[2] Currently, BSRIs are pervasive across different fields: particle accelerators and nuclear reactors now work alongside synchrotron radiation, neutron scattering, free-electron laser facilities, and neutrino telescopes to study materials science, chemistry, energy, condensed matter physics, nanoscience, astronomy, biology, biotechnology and pharmacology (Doing, 2009; Heinze and Hallonsten, 2017).

Policymakers have long recognized the strategic importance of scientific research as an important component to respond to increasing global competition towards economic and social development (Martin, 1995). This thesis was most famously espoused in the report of Vannevar Bush (1945), *Science: The Endless Frontier*. The 'Bush legacy' (Wilson, 1991) argued that investments in basic research were not only good for fundamental science but also generated applied engineering and technologies that translated to products, spin-offs, jobs, and economic prosperity that benefited all social classes. With the large investments required to build and maintain BSRIs, these secondary benefits became an important aspect of BSRIs, particularly with policymakers and the general public becoming critical of their expense. In response to this scrutiny, proponents of investments in BSRIs have focused on their value outside of their direct scientific purview (Autio et al., 1996), a precedence established by Lawrence's cyclotron that produced radioactive isotopes useful for cancer treatment (Hiltzik, 2016). Here, scholars have focused on the direct economic multipliers of procurement, technology development, standards, as well as the indirect notions of knowledge transfer, capacity building, and education (Autio et al., 2004; Florio and Sirtori, 2016; Salter and Martin, 2001; Scarrà and Piccaluga, 2020; Schopper, 2016).

There are numerous examples of the technology innovations frequently celebrated as secondary benefits of BSRIs (Organisation for Economic Co-operation and Development (OECD), 2014). The most famous case was the World Wide Web (specifically HTTP, URL, HTML) when Tim Berners-Lee convinced CERN's managers in 1993 to place it in the public domain and make the IP freely available to everyone. NASA[3] boasts over 2000 spinoffs since 1976; ESA[4] makes similar claims of spinoffs and technology transfer. Specific examples of unintended technology innovations from BSRIs include NASA's viscoelastic foam that was commercialized in the mattress industry as memory foam (Schmidt, 2009); or White Rabbit (CERN), a clock and event system to synchronize time measurement at the nanosecond level which has been adopted in financial services, telecommunications networks, automated vehicles, central navigation systems for air traffic control, IoT, and smart grids (Priego and Wareham, 2018).

Despite numerous success stories, cultivating innovations from BSRIs can be challenging given the uncomfortable symbiosis between science and business. For instance, in Europe, policymakers have long been concerned with resolving the European paradox – the idea that Europe excels in basic science but not in commercializing science into marketable innovation (Dosi et al., 2006). The most frequently cited frictions include two conflicting cultures (Hammett, 1941). For many scientists, any mention of financial or material compensation is considered a debasement of the moral ethos of the scientific enterprise. An additional challenge is the different clock speeds at which the two endeavours operate: the normal life cycle of much science spans many years, if not decades; the normal financial payback window for the venture capitalist is 24–48 months (Anderson et al., 2012). This is exacerbated by the fact that the technologies within these infrastructures are often in the realm of deep tech. Deep technologies typically operate with numerous interdependent components in a larger system that require careful orchestration across the different actors and standards. This demands larger capital investments, longer development times, and a more patient investor outlook to navigate the long path towards commercialization.

The limited literature on serendipitous innovations from BSRIs has described anecdotal cases largely as accidental outcomes. However, it has been less comprehensive in delineating the antecedent conditions and purposeful interventions that can be implemented to increase its likelihood. This fact, combined with the special nature of the deep technologies that originate from BSRIs, motivate a specific analysis of the nature of serendipity and how it can be proactively cultivated in this context. We divide this into two main research questions:

- How do researchers at BSRIs generate alternative applications of their technologies?
- What is the role of an initiative like ATTRACT in enabling the various activities towards serendipity?

3. Data and methods

We collected data for this analysis in three phases. We first conducted exploratory interviews with managers of BSRIs and reviewed the extant literature to identify factors relevant to serendipity in the context of BSRIs. We then analyzed the 170 project proposals to identify the modes of serendipity within the funded projects. We augmented the project data with a survey of project owners to examine the efficacy of the serendipity triggers induced by ATTRACT. Our final analysis phase combined the data sets to regress the modes and determinants of serendipity for additional insight. We summarize the steps in Fig. 1.

3.1. Setting: the attract project

The authors of this paper are involved in the ATTRACT project. ATTRACT is a €20 M initiative funded by the European Commission that aims to systematize the discovery of breakthrough applications from the continent's research infrastructures (European Commission, 2016). It brings six of the largest European scientific research infrastructures, members of the EIROforum: European Organization for Nuclear Research (CERN), European Molecular Biology Laboratory (EMBL), European Southern Observatory (ESO), European Synchrotron Radiation Facility (ESRF), European X-Ray Free-Electron Laser Facility (European XFEL), and the Institut Laue-Langevin (ILL). These organizations work in diverse domains such as nuclear, particle, and condensed matter physics; life sciences; molecular biology; astronomy; materials science; structural biology; and chemistry.

ATTRACT was designed to leverage the pre-existing relationships between research infrastructures and their industrial suppliers; that is, the highly specialized SMEs that have contributed to the engineering, construction, and operation of BSRI technologies, towards the ineffectual transition between the technology-push instruments and the market-pull instruments typically employed in innovation policy (Auerswald and Branscomb, 2003; Cunningham et al., 2013; European Commission, 2016; Wolfe et al., 2014). As BSRI technologies have already been developed and operated at scale, the technologies are substantially de-risked compared with greenfield technology

[2] Quoting Luis Alvarez in Hiltzik (2016): There were no doors inside the Rad Lab. 'Its central focus was the cyclotron, on which everyone worked and which belonged to everyone equally (though perhaps more to Ernest). Everyone was free to borrow or use everyone else's equipment or, more commonly, to plan a joint experiment'. The team approach to physics, Alvarez judged, was 'Lawrence's greatest invention'. (Hiltzik, 2016:129–30).

[3] https://spinoff.nasa.gov/database/.

[4] https://www.esa.int/Applications/Telecommunications_Integrated_Applications/Technology_Transfer.

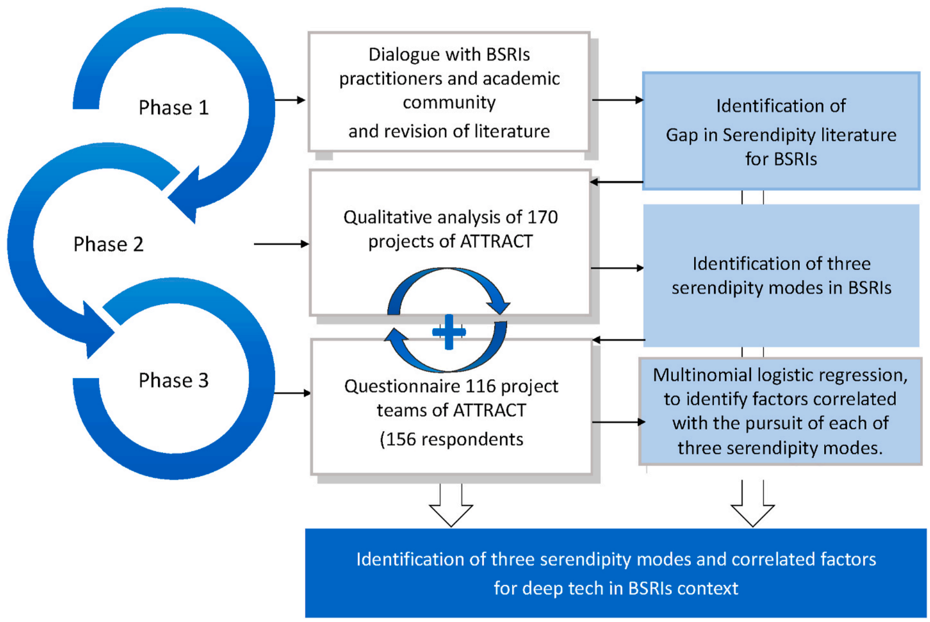

Fig. 1. Methodological approach.

development. While there are no 'intended' applications or desired outcomes, there are some obvious areas where BSRI technologies can be employed. These include medical devices and imaging technology, biotechnology, energy, advanced manufacturing, automation, micro-electronics, materials and coatings, environment and sustainability, and information and communication technology. The ATTRACT project is designed to facilitate innovation across three main dimensions: *social* (stakeholder networking), *temporal* (meet unique timing needs of deep tech), and *systemic* (systemic exploration of connections and combinations.)

Table 3 highlights the main attributes of ATTRACT and how they are positioned relative to traditional EU funding instruments and private capital investments.

An open call was launched to solicit project proposals from 1 August 1 to October 31, 2018. While not exclusive, the emphasis was on concepts at technology readiness levels 2–4. The call solicited proposals leveraging four main technology groups: a) sensors; b) data acquisition systems and computing; c) software and integration; and d) front- and back-end electronics. 1211 submissions were received. The top 10 countries submitting applications were: Italy (261); Spain (230); Switzerland (108); France (96); United Kingdom (81); Germany (67); Finland (65); Netherlands (59); Portugal (33); and Austria (26). All submissions were assessed by an independent scientific committee on technical merit and innovation potential. Specifically, the evaluation dimensions included project definition, scope, and technological feasibility, technology state-of-the-art, scientific/engineering merit, industrial potential, commercial feasibility, and social value.

From these submissions, 170 projects were awarded €100,000 for the development of a proof-of-concept or prototype with an application outside of the original purview of the technology over one year.

Table 3
Comparison between ATTRACT and other funding instruments.

	ATTRACT	EU range public funding instruments[a]	Private instrument
Approach for crossing the valley of death	Considers that breakthrough technologies need two steps of risk absorption and risk mitigation	Assumes that only one step is needed – normally risk mitigation (projects are funded on equal footing)[b]	Focuses on relatively low-risk technologies with no need for risk absorption
Risk absorption (reduce large TRL gap)	Public seed funding to foster ideas with breakthrough potential (100k EUR). ATTRACT[b] aims to continue with public scale funding for selected projects (2 M EUR)		
Risk mitigation (close TRL gap)	Public/private investment mechanisms [c]	Public/private investment mechanisms	Angel, Venture capital funding
Pre-competitive market	Ensured in projects with participation of research infrastructures	Not ensured and depending on a project-by-project case	Not ensured
Scaling up	Late-stage VC funding instruments, private equity, IPOs, etc.		

[a] We are referring to EU funding programs such as Horizon 2020. We do not consider national public funding programs.
[b] Exceptions exist such as the SME instrument https://ec.europa.eu/programmes/horizon2020/en/h2020-section/smeinstrument. Nevertheless, they differ from ATTRACT because a project needs to apply for seed funding, and subsequently, for scale funding. In ATTRACT the transition between seed and scale is streamlined.
[c] http://www.eif.org/; http://www.eib.org/en/index.htm.

3.2. Analysis of project proposals

In the first phase of this study, we perform qualitative coding of the 170 proposals to identify the forms in the pursuit of serendipity as well as other proxies of market readiness and technological feasibility. Each proposal submitted contained a maximum of 3000 words, including the following parts: a) summary; b) project description; c) technology description and external benchmarks; d) envisioned innovation potential (scientific and/or industrial) as well as envisioned social value; e) project implementation, budget, deliverables, and dissemination plan.

For each project proposal, we coded for the following variables on the partner composition: a) the number of countries involved; b) industry involvement; c) number of universities; and d) number of research organizations. For the project domain, we used the domain indicated by the projects in their submission as dummy variables: a) sensors; b) data acquisition systems and computing; c) software and integration; and d) front- and back-end electronics. We also read through each project to identify the applications areas of the different projects. We identified the following application areas: healthcare, diagnostics, biology, neuroscience, chemical analysis, environment, electronics, robotics, internet of things, particle physics, energy, security, manufacturing, communications and space science.

Three master's students with backgrounds in biomedical engineering, mechanical engineering and physics, and entrepreneurship evaluated each project separately. They coded for the following project characteristics: technology readiness level (TRL) (scale of 1–9), the scope of market application (specific, specific but easily expandable, or general), location in the value chain (upstream or downstream), technology novelty (scale of 1–5), technology relevance to market (scale of 1–5) and credibility of budget and milestones (scale of 1–5). After analyzing each project separately independently, their findings were integrated. In cases where the codes were not consistent, discussions were held to reach consensus. The coding was then validated in an additional round of coding by the authors. As such, each project was evaluated and coded by a minimum of three independent evaluators. In addition, three physicists and a venture capital expert oversaw the coding process and validated the results.

In the project text, researchers typically narrate the form by which they were able to come up with new applications for their scientific research. We coded these descriptions and identified higher-level codes that capture these descriptions (Fig. 2). Through an iterative process, we identified four recurrent themes by which serendipitous discoveries were actively pursued by scientists in our first reading of the 170 projects.

In the second and third reading, we categorized the projects according to these criteria:

- *Extending extant research* (baseline) – technologies from previous research work are extended or improved to be more effective or efficient but still within the same domain or application area.
- *Combination of different technologies* – technologies or knowledge from different research domains are combined, integrated, or assembled to produce a new application.
- *Applying technology to another field* – technology or knowledge from one domain is used in a new research domain or application area.
- *Using machine learning or artificial intelligence* – when the computational advances in machine learning or artificial intelligence are used to extend or find a new use for existing technologies.

Note that we do not consider extending extant research as a mode of serendipity as it describes the normal way that scientists advance their research. We have therefore used it as a baseline in our statistical analysis. We are more interested in the three path-breaking modes. Each project can apply these different modes with varying emphasis. As such, for each project, we choose the mode that they emphasize the most in their text.

3.3. Questionnaire

To understand how ATTRACT facilitated serendipity in the 170 projects, we administered a survey to the 170 project teams. This questionnaire was designed from input from the various stakeholders in the project and consulting the management literature on themes related to commercializing breakthrough technologies. The questionnaire design underwent three iterations to ensure its coverage and comprehensibility. The relevant questions in this study are in Appendix 3.

The questionnaire was administered through the survey software Qualtrics. It was distributed to the project members of the funded projects from August to September 2020. The questionnaire was completed by 152 respondents representing 116 unique projects, corresponding to a response rate of 68% of the 170 projects. For the data analysis, we had to do additional processing since some projects had multiple respondents. For questions that asked respondents to tick different activities, if one respondent ticks an answer for the project, we consider it as a response for the entire project.

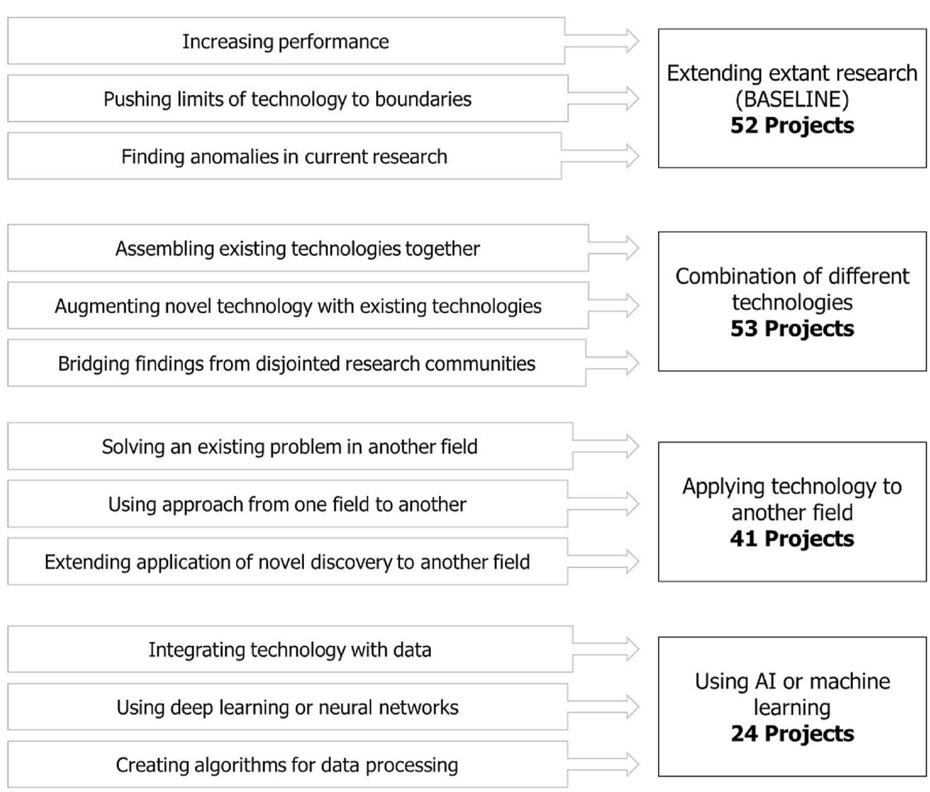

Fig. 2. Data structure on the serendipity forms analysis.

4. Findings

4.1. Modes of serendipity emerging in BSRIs

In this section, we explore the various ways that researchers pursued alternate applications of their technologies as described in their project proposals. Note that these modes are neither exhaustive nor mutually exclusive, but rather, the primary activities that researchers in BSRIs conducted to find novel applications.

As a baseline, we found that many projects extended extant research (31%). Typically, this proceeds from re-examining previous research so that new features that have not been previously identified or explored can surface. For instance, some projects looked at the possibilities enabled if current detectors can be applied at extremely cold temperatures or environments with very high radiation. Similarly, some projects signalled new application areas by envisioning what opportunities can be created if the technology becomes a magnitude more efficient or powerful. As this is consistent with normal research development, we focus on three serendipitous processes pursued by technologists to come up with alternative applications.

4.1.1. Combination of different technologies

The most frequently represented form was the combination of different technologies (41%). Under this category, technologies could come from adjacent or distant domains. Moreover, these technologies could be combined in varying degrees of integration. On one extreme, we identify a subset of projects (16%) where existing, readily available technologies are assembled to come up with a new application. For instance, a project called PHIL which aims to use a photonic system for liquid biopsy mentions that:

> "we will design and build the system using mainly commercial solutions for the different system aspects."

Otherwise, many projects combine the latest advances from distant research areas to create novel solutions. A notable example is the SCENT project which aims to create new gas sensors. The project mentions that it is:

> "based on merging two up-to-now disjointed macro-disciplines: high-pressure technology and gas-sensing; whose scientific communities are still far one another: the former focusing mainly on synthesis of materials, the latter unaware of HP-potentialities."

4.1.2. Applying technology to another field

Another set of projects (27%) applied technology from one field to another field. This category coincides best with the previous notions of serendipity – finding new uses from existing things. By exposing the technology to a field that it has not been previously used for, new use cases for the technology potentially emerge.

A notable example of a project is SIMS, designing a seismic imaging and monitoring system. They mention that they will develop:

> "next-generation MEMS sensor that utilizes patented technology inspired by the search for gravitational waves."

4.1.3. Using artificial intelligence or machine learning

The final form we identified involved the application of AI or ML for a specific application, accounting for 14% of the projects. This category can be considered a subset of the previous category since AI or ML originates from the computational sciences that are finding new uses in different domains. By being able to find patterns that humans cannot easily identify, it can be said that applying AI or ML increases the efficacy of various sensors in what they can get from the data collected.

Many of the projects in this category are in the field of healthcare. The usage of ML allows data collected from the various imaging technologies to be brought together and processed to reveal new insights on certain diseases. For instance, the project MAGres plans to integrate various magnetic resonance techniques to get a better understanding of the brain tumour glioblastoma. They mention that:

> "ML [machine learning] methods are the key to unlock the predictive power from the complex and high-dimensional data to be acquired"

4.2. Role of ATTRACT in cultivating serendipity

We augment our project data with the survey results and discuss them according to three dimensions that cluster the role of ATTRACT in cultivating serendipity:

a) Social dimension: generation of networking opportunities among different stakeholders,
b) Temporal dimension: support at the appropriate time, and
c) Systemic dimension: systematically cultivating different connections and combinations.

4.2.1. Social dimension

To promote serendipitous interactions between different organizations, ATTRACT established a requirement for the participation of at least two organizations. While the majority of projects only had two organizations collaborating, as many as five organizations can be seen collaborating in a single project (summary in Fig. 3A).

Each ATTRACT project brings together a different set of organizations with complementary sets of competencies towards finding new applications of big science research. As seen in Fig. 3B, the majority of projects involve research organizations (ROs) or universities. Many projects also involve input from industrial partners including start-ups, small and medium-sized enterprises (SMEs), or multinational corporations (MNCs). The most frequent configuration involves collaboration between universities and research organizations (Fig. 3C). These research organizations typically have expertise in spinning out technologies. Aside from this configuration, industry-academia collaborations are extremely common, most notably between universities and SMEs and ROs and SMEs.

Exploring the countries represented in each project funded in ATTRACT, Fig. 3D shows that the majority of projects involve collaborations between organizations located in the same country. Such arrangements allow the partners to closely interact and meet frequently as they work on their projects. Interestingly, almost half of the projects (45%) involve international collaboration. One possible explanation is that for highly specialized projects requiring scarcely available expertise, collaborations must occur across borders.

4.2.2. Temporal dimension

The survey asked the teams to identify the timing of crucial milestones concerning ATTRACT. This provides us some evidence from which we can infer the particular role and timing played by the initiative for the different projects. The responses are summarized in Fig. 4A. A working hypothesis in the formulation of ATTRACT was that it could have sparked new ideas for scientists in BSRIs. However, as seen by the questionnaire, most respondents already had the idea before the ATTRACT call (87%). Given that most of the ideas existed before the ATTRACT call, we see that 72% of the respondents were already looking for funding for their idea even before the ATTRACT call was published. Similarly, 39% of the respondents have already worked on their projects in some capacity before ATTRACT. This supports the argument that these scientists and engineers working at BSRIs have ideas that are the result of the day-to-day work but possibly require additional resources to advance them. Nonetheless, it is still interesting to see that there have been a small number of project ideas that were "activated" by the call for

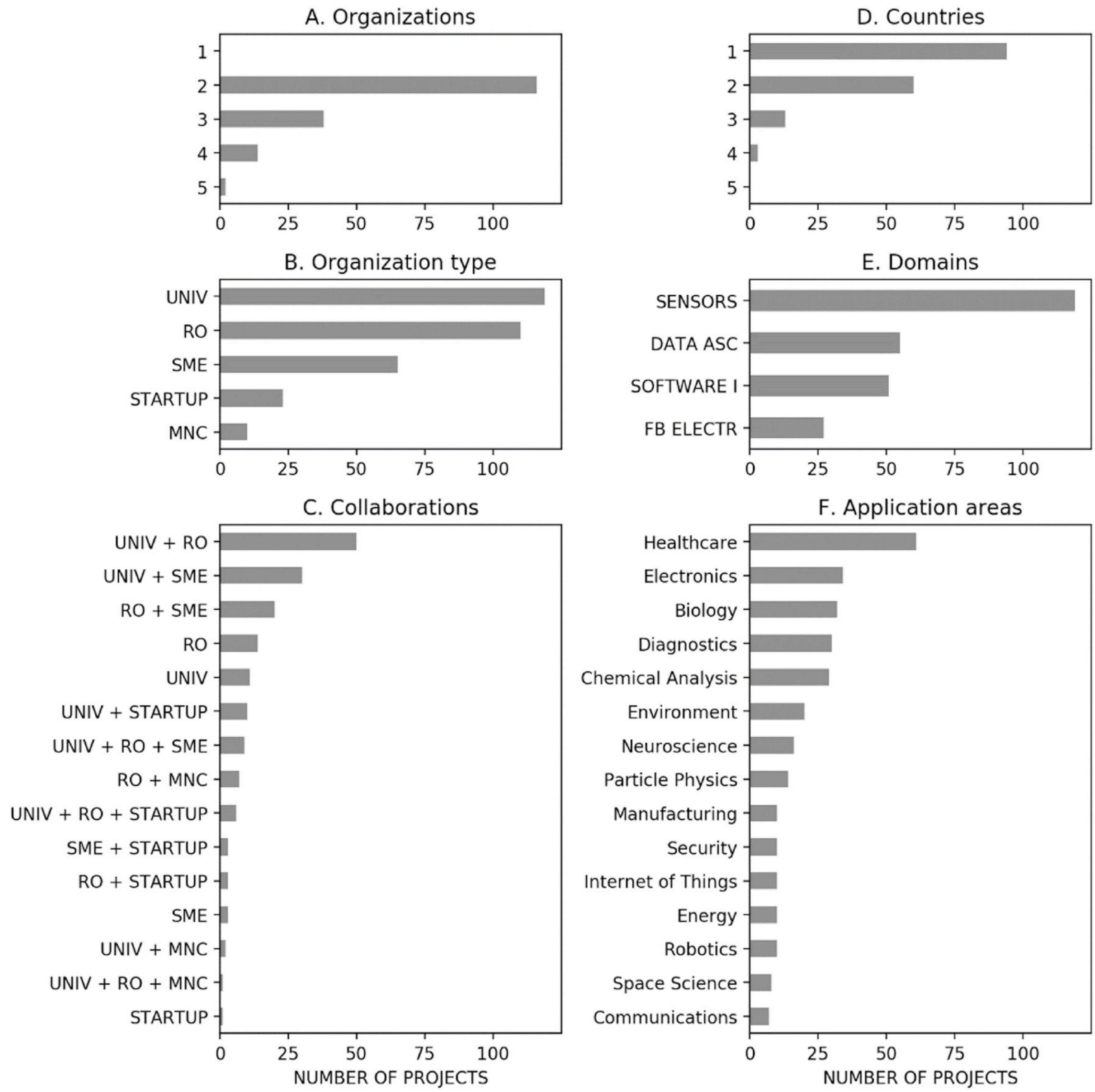

Fig. 3. Summary of Projects involved in ATTRACT projects. A shows the number of organizations collaborating across projects. B shows the type of organizations collaborating per project: University (UNIV), Research organization (RO), Small-medium enterprise (SME), Startup (STARTUP), and Multinational company (MNC). C shows the combinations of organizations collaborating in a project. D shows the number of countries collaborating across projects. E shows the domains: Sensors (SENSORS), Data acquisition systems & computing (DATA ASC), Front & back-end electronics (FB ELECTR), and Software and integration (SOFTWARE I). F shows the application areas as coded from analyzing the text.

project proposals.

The majority of respondents mentioned that they knew their teams beforehand at 82%. Many groups have also collaborated in other projects in the past at 61%. It is possible that many projects probably were funded in the first place due to their demonstrated synergy between the different groups engaging in these collaborations.

Hence, while we cannot eliminate the possibility that the projects would not have existed independently, we find substantial evidence on the importance of the unique arrangement of ATTRACT in enabling these projects to progress. For instance, a majority of the respondents mentioned how ATTRACT was a unique funding instrument (Fig. 4C). They also supported its focus on the applications of research and collaborations with the industry. Many respondents saw the potential in funding more projects in the early-stage phase as seen by the high rating. Furthermore, respondents supported giving larger funding to successful projects in the first phase of ATTRACT.

4.2.3. Systemic dimension

Fig. 3E shows that ATTRACT projects come from different technological domains: sensors (70%), data-acquisition systems and computing (32%), software and integration (30%), and front and back-end electronics (16%). Note that the projects can belong to more than one domain so they do not add up to exactly 100%. As seen, a large percentage of projects are in the domain of sensors. This is not unexpected as BSRIs are generally known for the sophistication of their imaging and detection technologies. Moreover, as shown in Fig. 3F, ATTRACT caters to a diverse range of application areas including healthcare (36%), electronics (20%), environment (12%), energy (6%), security (6%), and manufacturing (6%).

The diversity across project characteristics is also highlighted in Appendix 1. Projects are almost equally split in degrees of specificity in the application area (Appendix 1D). While there are 35% of projects stated a specific application area, there are also a large number of projects offering a general solution to different application areas (28%). An interesting category is the 38%, specific but expandable projects, that

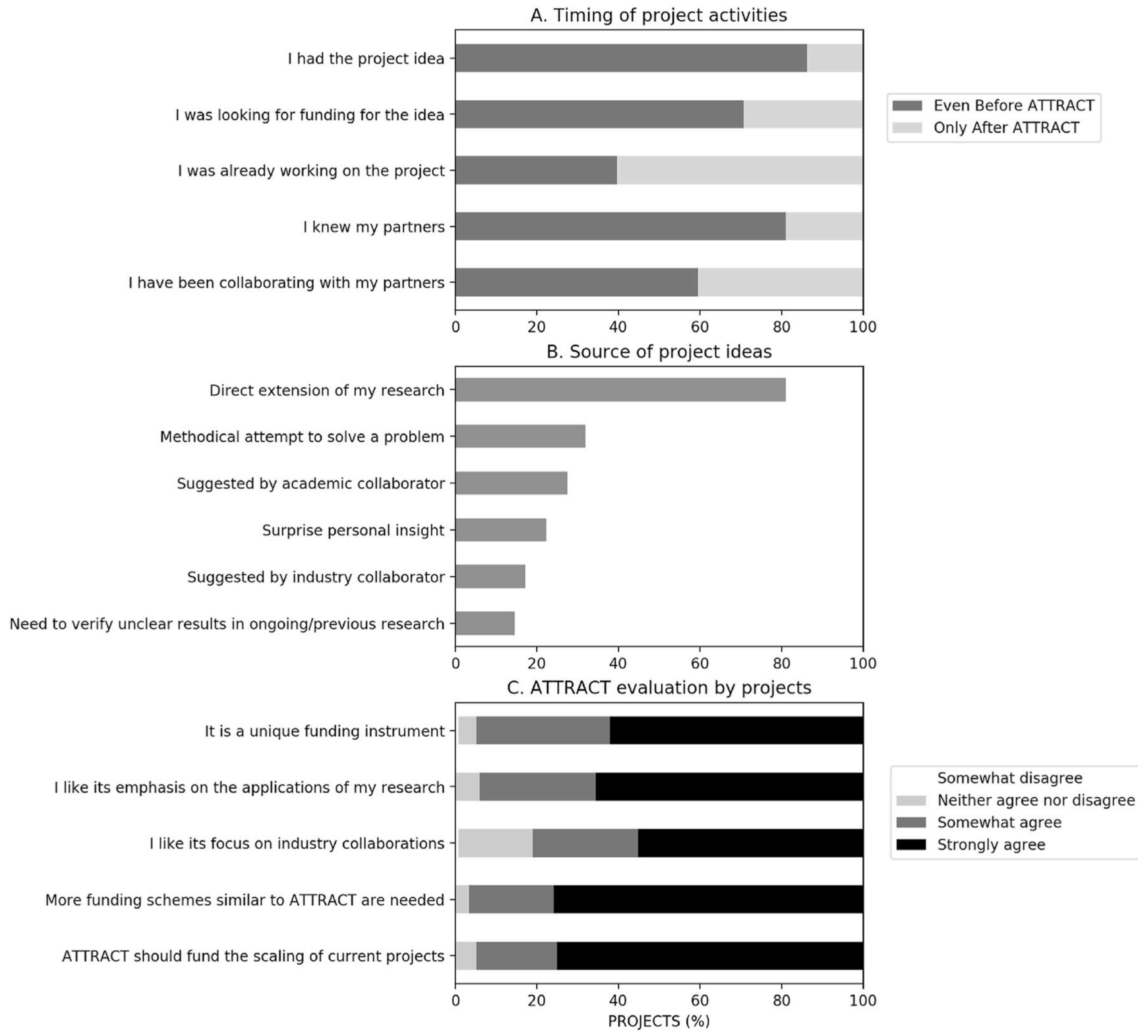

Fig. 4. Questionnaire results. Section A shows the timing of activities for the different projects concerning ATTRACT. Section B shows the source of project ideas. Section C shows the overall evaluation of ATTRACT pooled by the project.

have already identified their pilot market but then can easily extend their reach to other areas. Furthermore, Appendix 1E shows that there are slightly more projects located upstream in the value chain (55%) compared with downstream projects (45%).

Appendix 1C shows that the most common technology readiness level was 2, meaning that the projects are only in the stage where the technology and/or application area has been conceptualized. The average TRL across all projects was 1.8 correspondingly. These low TRL values are consistent with what was expected from the projects during the proposal call; that is, deep tech that requires developmental support to increase market readiness.

Appendix 1B shows that the projects are highly novel, with an average of 3.4 out of 5 ratings. The typical problem with technologies that are too novel is finding areas that are immediately relevant for their application. However, as seen in Appendix 1A the projects generally have high relevance to the market they are hoping to serve. Across all projects, the average was 3.5 rating out of 5. For projects with lower market readiness ratings, the support provided by ATTRACT enables these projects to refine their technologies to find a better fit with their market of choice or to find a more applicable market to which their solutions can be of value. To systematically explore the space in the development of their technologies, the project team needed to have a credible plan and a list of milestones. Appendix 1F shows that the projects were rated highly on this aspect, with an average of 3.5. out of 5 ratings.

When asked about the origin of ideas, we see that most ideas came as an extension of their research at 81% (Fig. 4B). Related to this, 14% of the projects mentioned that their idea came from anomalies from their research that needed revisiting. Consistent with traditional notions of serendipity, many projects appear to have originated from surprise personal insight at 21%. In contrast to this more burst-like emergence of an idea, there were also answers from teams reporting that their starting point was identifying the problem and that their project was a methodical effort to resolve this identified need (27%).

4.3. Relationship between antecedents and modes of serendipity

We subsequently combined the datasets to estimate two multinomial logistic regression (MLR) models to identify the antecedent conditions that enable each mode of serendipity to emerge. The dependent variables are the modes of serendipity. The independent variables are the different antecedents identified from the project proposals and questionnaire. The first model contained only the project proposal data (N = 170) (Table 4). The independent variables included partner composition, project evaluation, and application domain. The second model integrated the questionnaire results (N = 116) (Table 5). Apart from the previously mentioned three groups of independent variables, we also included the timing of activities and idea source for this second model. The variables are summarized in Appendix 2.

Multinomial logistic regression allows us to predict the probability

Table 4
Multinomial logistic regression of project proposals.

	Model A: Only project proposals (N = 170)						
	Dependent variable: Serendipity Base outcome: Previous research	Combine Tech		Apply to a different field		Use AI	
		β	RRR	β	RRR	β	RRR
Partners	Countries	−0.748	0.473	−1.113	0.329	−0.571	0.565
		(0.353)**		(0.423)***		(−0.460)	
	Industry involvement	−0.167	0.846	0.373	1.452	−0.118	0.889
		(−0.521)		(−0.583)		(−0.654)	
	University	−0.769	0.464	0.479	1.615	−0.042	0.959
		(−0.590)		(−0.600)		(−0.709)	
	Research Organization	−0.013	0.987	0.24	1.271	−0.264	0.768
		(−0.597)		(−0.626)		(−0.652)	
Project evaluation	Tech Relevance	−0.41	0.664	−0.707	0.493	−0.025	0.976
		(−0.414)		(−0.446)		(−0.465)	
	Tech Novelty	0.127	1.136	0.114	1.121	−0.223	0.800
		(−0.375)		(−0.401)		(−0.487)	
	TRL	−0.366	0.694	−0.43	0.651	−0.548	0.578
		(−0.442)		(−0.468)		(−0.563)	
	Credibility	0.249	1.283	−0.066	0.937	0.230	1.258
		(−0.316)		(−0.299)		(−0.389)	
	Generalizability	−0.366	0.694	−0.559	0.572	−0.147	0.863
		(−0.321)		(−0.341)		(−0.409)	
	Upstream	−1.232**	0.292	−0.008	0.992	−1.065	0.345
		(−0.542)		(−0.618)		(−0.691)	
Domain	Healthcare	0.488	1.628	0.431	1.539	0.874	2.396
		(−0.532)		(−0.563)		(−0.689)	
	Data acquisition systems & computing	0.728	2.071	1.260	3.525	1.486	4.418
		(−0.581)		(0.605) **		(0.661)**	
	Front & back-end electronics	0.483	1.620	−0.096	0.909	−0.425	0.653
		(−0.635)		(−0.656)		(−1.148)	
	Sensors	0.185	1.203	−0.335	0.715	−1.37	0.254
		(−0.592)		(−0.625)		(0.752)*	
	Software and integration	0.314	1.369	0.375	1.455	0.913	2.491
		(−0.583)		(−0.660)		(−0.649)	
	Constant	3.565		4.812		2.119	
		(2.134)*		(2.379)**		(−3.132)	
Obs							170
McFadden R^2							0.186
LR chi-square							87.40
Prob > chi2							0.000
Log-Likelihood							−184.497
Akaike crit.(AIC)							468.338
Bayesian crit.(BIC)							618.856

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Robust Standard errors in brackets

that a project belongs to a certain category by modeling the dependent variable as a logistic function of the independent variables (Borooah, 2002; Hosmer et al., 2013). This method aligns with our data as the dependent variable is composed of categories with no intrinsic ordering (Hosmer et al., 2013). MLR is considered appropriate given that normality assumption cannot be reasonably assumed for a dependent variable with unordered categories (Yoruk, 2019). In MLR, the dependent variable's first category is taken as a baseline (El-Habil, 2012). Hence, in our model, extending extant research has been chosen as the baseline category. The probability that project *i* belong to a serendipity category *c* is denoted by the following equation:

$$Prob(Y_i = c) = \left\{ \begin{array}{l} \dfrac{1}{1 + e^{\beta_0} + \Sigma_{k=1}^{k} \beta_k X_{kc}}; ifc = 1 \\ \dfrac{e^{\beta_0} + \Sigma_{k=1}^{k} \beta_k X_{kc}}{1 + e^{\beta_0} + \Sigma_{k=1}^{k} \beta_k X_{kc}}; ifc = 2, 3, 4. \end{array} \right.$$

where c denotes the serendipity category (1 for extending extant research, 2 for a combination of different technologies, 3 for applying technology to another field, and 4 for using AI); Y_i is the serendipity category to which the project *i* belong; *k* is the number of variables; $X_k$is a vector of explanatory variables; β_0 is the model's constant and β_k are the relevant coefficients.

In our results, we also report the relative risk ratios (RRR) or odds ratios that reveal the strength of the relationship. The RRR is obtained by exponentiating the multinomial logit coefficients. The positive and negative regression coefficients receive RRR >1 and RRR<1, respectively. A one-unit change of the corresponding independent variable would change the odds of the dependent variable belonging to a particular category, compared to a reference category. Data were analyzed using STATA.

As an initial test, we evaluated multicollinearity with a pairwise correlations matrix among independent variables. In this matrix we found that the majority of correlation coefficients were less than 0.30 among the explanatory variables, indicating that we do not have a severe occurrence of multicollinearity. In addition, the variance inflation factors (VIF) were checked. For both models, the VIFs were below 3, thus reinforcing a lack of multicollinearity. Tables 4 and 5 show a summary of the MLR results for Model A and Model B, respectively. The Likelihood Ratio Tests of Model A ($\chi^2 = 87.40$, $p < 0.001$) and Model B ($\chi^2 = 258.98$, $p < 0.001$) show a good model fit. Also, the values of McFadden's R2 allow us to conclude that Model A and Model B are characterized by relatively good predictive power, since the full model containing our predictors represents 18.6% and 40.2% improvement in

Table 5
Multinomial logistic regression including questionnaire responses.

Model B: With questionnaire responses (N = 116)							
	Dependent variable: Serendipity Base outcome: Previous research	Combine Tech		Apply to a different field		Use AI	
		β	RRR	B	RRR	β	RRR
Partners	Countries	−0.880 (0.669)	0.415	−2.211 (0.554)***	0.110	−0.617 (0.772)	0.540
	Industry involvement	0.034 (0.807)	1.035	−0.228 (0.918)	0.796	−0.163 (1.117)	0.850
	University	−1.991 (0.903)**	0.137	0.529 (0.863)	1.697	−0.770 (1.197)	0.463
	Research Organization	−0.316 (1.015)	0.729	0.198 (0.989)	1.219	−2.815 (1.306)**	0.060
Project evaluation	Tech Relevance	−0.394 (0.616)	0.674	−1.562 (0.699**)	0.210	1.925 (1.027)*	6.852
	Tech Novelty	0.026 (0.623)	1.027	0.419 (0.675)	1.520	−1.940 (1.098)*	0.144
	TRL	−1.078 (0.826)	0.340	−0.141 (0.588)	0.869	−0.907 (0.910)	0.404
	Credibility	0.368 (0.476)	1.445	−0.300 (0.432)	0.741	1.428 (0.719)**	4.172
	Generalizability	−0.097 (0.591)	0.907	−1.336 (0.539)**	0.263	−0.234 (0.724)	0.791
	Upstream	−2.239 (0.977)**	0.107	0.359 (0.916)	1.432	0.074 (0.963)	1.077
Domain	Healthcare	−0.517 (0.769)	0.596	−0.619 (0.723)	0.538	0.058 (1.103)	1.060
	Data acquisition systems & computing	2.391 (1.067)**	10.920	2.119 (0.998)**	8.326	2.491 (1.332)*	12.069
	Front & back-end electronics	−0.299 (1.003)	0.742	−0.723 (1.184)	0.485	−0.090 (1.493)	0.914
	Sensors	0.054 (0.995)	1.056	−0.334 (0.972)	0.716	1.049 (1.512)	2.856
	Software and integration	−0.505 (0.939)	0.604	−0.526 (1.083)	0.591	3.019 (1.132)***	20.470
Timing	Had the idea only after ATTRACT	−0.474 (1.302)	0.622	−3.067 (1.442)**	0.047	1.233 (1.862)	3.430
	Searched for funds only after ATTRACT	1.949 (1.083)*	7.020	2.344 (1.090)**	10.418	−1.738 (1.348)	0.176
	Worked on the project only after ATTRACT	0.031 (0.740)	1.031	−0.140 (0.643)	0.870	0.051 (0.933)	1.052
	Knew partners only after ATTRACT	−1.732 (1.205)	0.177	−0.747 (1.187)	0.474	−3.074 (1.848)*	0.046
	Collaborated only after ATTRACT	0.928 (0.942)	2.528	0.155 (0.825)	1.168	1.808 (0.950)*	6.100
Idea source	Direct extension of my research	2.129 (1.196)*	8.406	1.056 (1.133)	2.876	0.329 1.598	1.389
	Methodical attempt to solve a problem	−1.039 (0.942)	0.354	−0.203 (0.789)	0.816	2.625 (1.049)**	13.799
	Need to verify unclear results in ongoing/previous research	−2.567 (1.868)	0.077	−0.290 (0.945)	0.749	2.429 (1.405)*	11.345
	Suggested by academic collaborator	−0.164 (1.069)	0.849	−1.280 (1.052)	0.278	1.880 (1.129)*	6.555
	Suggested by industry collaborator	−2.093 (1.364)	0.123	−0.966 (1.082)	0.380	0.013 (1.272)	1.013
	Surprise personal insight	0.201 (0.862)	1.222	−1.375 (0.913)	0.253	−0.660 (1.199)	0.517
	Constant	4.598 (4.105)		10.455 (3.617)***		−5.992 (5.206)	
Obs							116
McFadden R^2							0.402
LR chi-square							258.98
Prob > chi2							0.000
Log-Likelihood							−93.804
Akaike crit.(AIC)							349.608
Bayesian crit.(BIC)							572.648

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Robust Standard errors in brackets

fit relative to the null model, respectively.

In the following, we discuss the antecedents we find for each mode. For each of these modes, we identify significant relationships with antecedents related to partner composition, project evaluation, application domain, timing of activities and idea source. These antecedents are not considered exhaustive, but they provide an early exploration of the various ways to promote the discovery of alternative applications of technologies from BSRIs.

4.3.1. Combination of different technologies

Our analysis offers a number of findings that are both expected and unexpected. To begin with, projects with more countries involved tend to combine technologies less. This outcome was counterintuitive assuming that combining technologies would require parties with different capabilities that are rarely present within one country (Kafouros et al., 2012). However, the higher coordination costs that are needed to collaborate between different countries might make this serendipity mode less likely to emerge (Stuart and Sorenson, 2003). Organizations with closer physical proximity can coordinate much closer to iron out how to combine disparate technologies effectively.

Projects that cater to downstream applications are less likely to combine technologies. This was unexpected since research has shown that downstream firms mainly benefit from combining such technologies (Ganco et al., 2020). However, this can be explained that projects focused on upstream technologies tended to advance the efficacy and applicability of individual technologies close to their origins in the BSRI with unspecified market applications. As such, we also see that universities, as peripheral partners, are less likely to be involved in projects that combine technologies.

Although we find that projects in data acquisition systems and computing involve combining technologies, it is surprising that combining technologies were not found in domains such as healthcare or front and back-end electronics, or idea sources such as suggested by industry collaborators. This insight suggests that for the deep technologies represented in the sample, the combinatorial explanation often advanced in innovation studies is less applicable (Arts and Veugelers, 2015; Fleming, 2001).

Projects that did not search for funding before ATTRACT tend to combine technologies. One potential explanation is that project teams from this mode may be pessimistic that their ideas may secure funding from an appropriate funding source. We can speculate then that many projects like these would have seized to exist without support from an external funding instrument.

4.3.2. Applying technology to another field

Similar to combining technologies, we find that the number of countries involved in a project has a negative relationship to applying technologies to a different field. This might reflect a preference to work with local partners in these project forms that require fast, incremental iterations of testing and development (Whittington et al., 2009). On another note, we would have expected to find more significant relationships with this category and industry involvement, assuming that this mode of serendipity requires a partner that will direct a technology towards a specific field of application (Stuart et al., 2007).

Moreover, we would have expected this mode to mostly be downstream technologies, but we do not find any relationship. This means that this mode does not necessarily mean applying technology to a specific application domain, but also can be related to using technology from one research field to another field, all being upstream.

Apart from this, all the other project evaluations are in line with expectations. We expected a negative relation with the relevance of the technology; when a technology being transferred from one field to another, it is uncertain whether these technologies are indeed appropriate for the new field (Hanisch and Rake, 2021). Similarly, we expect technologies to be less generalizable when they are transferred to a different field, as it caters to a specific usage within that new field (Andriani and Kaminska, 2021).

When it comes to the application domain, the strong positive relationship we find between data acquisition and computing with applying to a different field agrees with intuition. Originally, data acquisition and computing techniques are frequently unbound to specific technological artifacts or processes, increasing their cross-field applicability (Austin et al., 2012). As such, these systems can easily be transferred to another field towards a specific use.

Projects teams that had their idea before ATTRACT tend to apply technologies to another field. This is expected since it is not easy to pivot to applications outside of their primary field. Teams need to have thoroughly thought of new applications in their daily work, even before an instrument like ATTRACT comes. However, it is interesting that project teams that apply technologies to a different field tend to not search for funding before ATTRACT. Similar to combining technologies, this suggests that project teams seem to think that such a form of serendipity would not be easily fundable and thereby discourage teams from looking for funding that supports such innovative projects.

4.3.3. Using artificial intelligence or machine learning

We find many significant relationships with the application of AI or ML in the project evaluations. First, higher technology relevance is attributed to AI projects. Similarly, we see projects that have high credibility tend to apply AI. In line with this, instead of overselling artificial intelligence in terms of its novelty, these projects tended to be rated lower. In other words, project teams integrating AI tend to temper expectations on what they can deliver. In terms of the mix of partners, we find that research organizations tend to not be involved with artificial intelligence projects. This agrees with an explanation suggesting that artificial intelligence is mainly accessible to industry counterparts that have adequate data to train models based on downstream applications (Ahmed and Wahed, 2020).

Data acquisition systems & computing and software were, unsurprisingly, positively related to artificial intelligence. Curiously, sensors tend to be negatively related to artificial intelligence. This finding might reflect the fact that sensors are developed to detect and measure physical phenomena. The further processing and analysis of the collected data are performed by technologies in the data acquisition and computing category. In other terms, the semantic definition of the categories influenced this distinction.

In terms of timing, we find that projects wherein partners only knew each other after ATTRACT tend to not pursue artificial intelligence. This might suggest that integrating AI is not something that teams can easily implement without much thought (Haefner et al., 2021). However, if partners knew each other but only started to collaborate for ATTRACT, they tend to integrate AI. One interpretation for this is that ATTRACT enables project teams to pursue research lines that they would not have otherwise pursued without the funding provided by ATTRACT. AI is one of those modes of serendipity that project teams only had the luxury of following due to the project funding.

As for the idea source, we find that AI projects tend to be created to deliberately address a problem. Once again, this is in line with previous evaluations of artificial intelligence being highly relevant to their proposed projects. A final interesting finding is that artificial intelligence was pursued when scientists wanted to gain a better understanding of unclear research results. This is not surprising as artificial intelligence is known to be useful in making sense of information (Liu et al., 2020; Loureiro et al., 2021).

5. Discussion

This study asked two specific research questions exploring how researchers at BSRIs generate alternative applications of their technologies, and the role of an initiative like ATTRACT in supporting the various activities that enable serendipity.

In the first phase of analysis, we used data from the project proposals to identify modes in the pursuit of serendipity in BSRIs. We found that in their daily work, scientists and engineers working in BSRIs often develop novel ideas about alternative uses of technologies that could be potentially commercialized. They take the forms: (1) a combination of different technologies, (2) applying technology to another field, and (3) using AI or ML. In general, the serendipity modes identified are largely consistent with processes identified in the innovation literature. Hence, where an initial contribution of this study is mapping these modes to the extant serendipity literature, a larger contribution is the identification of the factors highly determinative to the unique cultures and technologies common in BSRIs. These insights further inform policy recommendations to facilitate alternative applications of BSRI technologies.

We summarize the most important relationships identified in our combined analyses in Table 6 and qualify them in continuation.

Our study reinforces the role of social interactions in serendipity. It is long known in the serendipity literature that social relations with a wide range of actors are necessary to increase the chances of unexpected encounters occurring (Busch and Barkema, 2020; Lane et al., 2019; Murayama et al., 2015). While it is important to promote collaborations, one surprising insight was that projects with more countries involved are less likely to combine technologies and apply a technology to another field. This emphasizes the importance of geographic colocation and clustering when it comes to innovation (Stuart and Sorenson, 2003). As projects scale up and increase their TRL and market readiness, further studies are needed to understand the role of social networks in commercialization.

However, we find only moderate evidence that ATTRACT brokered the creation of new ties among BSRI researchers. Additionally, we find limited support for the idea that ATTRACT sparked new ideas that scientists would have not had otherwise thought of, as most respondents claimed to have had their ideas even before the call for projects. We also find limited support that an initiative like ATTRACT motivated scientists to think of the market applications of their research. Most scientists were already looking for funding on their ideas even before the ATTRACT. Beyond the funding that enabled the development of a proof of concept, the additional benefits of ATTRACT were largely centred on the collaboration across complementary sectors and technological domains; that is, brokering relationships with industrial partners that facilitated the application of technologies in domains outside of the immediate purview of BSRIs.

Our study also contributes to the role of timing in spurring innovation. Different ideas have various windows of opportunity and require support at the appropriate times (Vértesy, 2017). This challenge is complicated in generalized programs like ATTRACT that deal with heterogenous technologies with diverse development cycles. Moreover, appropriate timing is particularly germane to funding interventions. Our survey results suggest that ATTRACT supported project development by providing resources to advance the technological feasibility of their ideas towards a valid proof of concept. This focus on early-stage feasibility is consistent with the maturity of the projects in the initial phase of ATTRACT, representing early-stage, high-risk, technologies with longer and more complicated development cycles. In this respect, we find that many researchers rated the initiative as a unique one compared to other funding sources, particularly compared with more traditional funding instruments that support initiatives with higher market readiness levels.

Table 6
Relationships found between modes and various antecedent conditions.

Modes	Significant relationships identified
Combination of different technologies	- Number of countries - Upstream market application + Data acquisition systems and computing + Searched for funds only after ATTRACT + Extending research
Applying technology to another field	- Number of countries - Technology relevance to the market - Generalizability + Data acquisition systems and computing + Had the idea even before ATTRACT + Searched for funds only after ATTRACT
Using artificial intelligence or machine learning	- Involvement of research organizations + Technology relevance to the market - Technology novelty + Credibility of budget and milestones + Data acquisition systems and computing + Knew partners even before ATTRACT + Collaborated with partners even before ATTRACT + Need to verify unclear results + Methodical attempt to solve a problem + Suggested by academic collaborator

Taken together, a holistic interpretation of these findings suggests that there is no lack of compelling ideas at BSRIs. As such, policy interventions intended to support idea genesis or cross disciplinary relationships across scientists, where valuable, are less critical. Rather, the relationships that matter are with industrial and partners that could provide the much-needed complementary skills in later-stage product development and commercialization. It also follows that financial or educational support should be focused on subsequent developmental phases.

As alluded to by the title of our article, the main role of ATTRACT was to systematically explore applications of research within BSRIs. To do this, ATTRACT funded projects from heterogenous domains with varying levels of maturity, novelty, relevance, and generalizability. Previous literature has elaborated how serendipity is the product of systematic exploration across a wide range of options (Fink et al., 2017; Martin and Quan-Haase, 2017; Napier and Hoang Vuong, 2013). Our research echoes this theme, departing from a romanticized ideal of flash-insight. Rather, in our context, serendipity resembles something more closely related to a protracted, partially controlled process with high uncertainty.

5.1. Deep technologies

An additional qualification for serendipitous innovation in BSRIs is the nature of the deep technologies that have specific attributes that render their innovation processes different from what is normally characterized in the literature.

First, the technologies generally have a very high level of technical specialization and sophistication. This may render their immediate or apparent application in other domains less evident. At a minimum, the fact that deep technologies often function in larger technical systems characterized by high complexity and interdependence can render their alternative applications less apparent due to the longer and more complicated development cycles.

Second, as deep technologies are enabling technologies encompassing sensing, imaging, detection, connectivity, computation, inference, actuation, and control (Siegel and Krishnan 2020), they are, by definition, further afield from immediate downstream or consumer-facing applications. Both of the characteristics (i.e. enabling and interdependent) stand in contrast to much of the serendipity literature that has focused on relatively independent, consumer-facing innovations.

Finally, the role of AI, ML and data acquisition systems & computing are prominent in deep tech. This is a result of several factors. First, most deep technologies are highly data-centric: they often generate, register, measure, or analyse data as a core function. However, it is important to make a distinction that in our sample, AI and machine learning were mainly used to improve the efficacy of the technology, not for discovering new applications. With the ongoing progress in these technologies (as in recommender systems or generative computing), it would be interesting to see how artificial intelligence and machine learning can directly be used to generate leads for serendipitous connections between various topics as an analytical intervention (e.g. Arvo, 1999; Giles and Walkowicz, 2019).

5.2. Implications for policy and practice

The main policy implication that emerges from our study is that scientists and engineers develop many new ideas about novel potential applications of BSRI technologies in their daily work. ATTRACT was most valuable in providing the crucial resources for these projects to move forward. Moreover, the project conceptualizations represent technologies with low TRLs: upstream technologies with a wide range of potential applications and substantial novelty. We did not find substantial evidence that ATTRACT triggered new ideas. Rather, that the main value to the project owners is in facilitating project development through financial resources, brokering relationships with industrial partners, and facilitating the applications in domains outside of the immediate purview of BSRIs.

The ATTRACT project is consistent with calls by Mazzucato (2016) who argues that the government can go beyond its role as a regulator or fixer of markets towards an entrepreneurial role, absorbing risk in strategic sectors until technologies have reached a sufficiently mature state to be attractive to private and venture capital. This assumes that market mechanisms and private capital alone may not be the most efficient route to realizing innovation via basic to applied research (Martin, 2016). Specific industrial policies and stimulus instruments are needed to absorb risk in basic research settings when working with low TRL technologies. This is particularly relevant in light of empirical research suggesting that the more the research infrastructure is involved in basic research as part of its mission, the less likely it that the organization will be involved in technology transfer activities (Boisot et al., 2011; Rahm et al., 1988); and this is certainly the case for several ATTRACT partners.

ATTRACT also resonates with the 'cooperative technology' model of technology transfer described by Bozeman (2000) that assumes government laboratories and research infrastructures can play an important role in technology innovation and economic growth. With some variation, authors such as Mazzucato (2013, 2016) and Bozeman (2000) echo the original doctrine of Vannevar Bush, that basic research has a substantial and positive impact on socio-economic innovation via direct and indirect mechanisms. Interestingly, however, recent literature has argued that while it is commonly believed that Bush maintained an unquestioning faith in an integrated and linear model of innovation, his notion was more sophisticated and involved symbiotic cross-fertilization (Leyden and Menter, 2018). In this view, the authors argue that while Bush saw that basic and applied research benefit each other, they also succeed by working as separate systems, or stacks. Consequently, scientific and economic policy mechanisms should seek to coordinate the two systems, allowing each to operate through its logic and success criteria, yet simultaneously cultivating specific points where they can nurture each (Cunningham et al., 2013; European Commission, 2016; Leyden and Menter, 2018).

5.3. Limitations and future research

As in all studies of this nature, ours has several limitations that can inform future studies. The most significant limitation is that our data are based on the 170 project proposals that were selected from a larger submission pool of 1211. Any possible selection bias introduced from this fact should be considered in the interpretation of the findings. Second, the survey instrument is self-reported responses and is not cross-validated against other data sources. Third, in the multinomial logistic regression, the second model incorporating the questionnaire responses had a smaller sample size despite containing more explanatory variables. Finally, faithful to its genesis in scientific institutions, ATTRACT should be seen as an experiment in innovation policy (Bakhshi et al., 2011) and a thorough evaluation of the efficacy of its mechanisms will require additional time before conclusive, outcome data are available.

This study is just one of the early empirical examinations of how BSRIs come up with alternate applications for their technologies. As such, there are many areas for future research. First, projects funded within the project can be followed for longitudinal studies to see their future commercialization prospects. Second, experimental studies and randomized controlled trials can also be done to further disentangle the various conditions that enable serendipity to occur. As we focused on the European BSRIs, comparative studies with their counterparts in other regions such as the United States would also be fruitful. Finally, much more conceptual work is needed to understand how to evaluate and promote the impacts of BSRIs apart from their capability of producing alternate applications, that do not endanger their primary scientific mission.

6. Concluding remarks

Our research contributes to extant research on technology transfer and innovation by analysing specific characteristics of BSRIs and how these can be embraced to increase their larger socio-economic value. Specifically, we contribute to the serendipity and innovation literature on three dimensions. First, the projects under ATTRACT allow us to probe serendipity in a quasi-experimental setting with a large data set and natural controls, extending innovation literature based on small sample sizes. Secondly, our analysis allows us to examine the specific characteristics of serendipitous innovation at BSRIs given their unique cultures and institutional logics. Finally, we focus on the attributes of deep technologies predominant at BSRIs. As highly sophisticated and enabling technologies far from immediate market applications, the modalities and processes of serendipitous innovation differ from the common empirical base of the innovation literature. Our study identifies some of these properties to understand their implications for scientific and innovation policy.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.technovation.2021.102374.

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