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Problem exploration for creating value propositions when developing point-of-care solutions

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ABSTRACT

Point-of-care (POC) testing has been increasingly proposed as one of the most promising solutions for improving healthcare provision as it enables fast and accurate testing both inside and outside hospital settings. Many of these POC device stem from academic research. Yet, the commercialization of these devices through academic spin-offs is not straigthforward. Many academic spin-offs fail due to an inproperly articulated value proposition. To create a value proposition with biosensors it is crucial to understand how they can be used to address problems in the current diagnostics processes and protocols. Therefore, this paper studies how different university teams engage in problem exploration to better understand how they can translate the technical features of their POC testing solutions into an attractive value proposition. To be able to study this, a qualitative case study research design was chosen. In particular, 11 university student teams participating in the SensUs contest were studied. The main findings show that teams adopting search patterns involving a 'broader' (i.e., considering a wider range of problems and stakeholders) and a more 'interconnected' (i.e., thematically linking problems with one another) problem-exploration were more successful in creating contest outcomes (biosensing solutions) with greater commercial viability. Moreover, teams that sougth direct feedback from market experts generated more commercially viable projects than teams that relied primarily on advice from technical experts.

1. Introduction

Point-of-care (POC) testing has increasingly been proposed as one of the most promising solutions for improving healthcare provision as it enables fast and accurate testing both inside and outside hospital settings. Over the past two decades, the demand for POC testing solutions has risen to an all-time high and is expected to even accelerate further in the coming years ("Point of Care Diagnostics Market Size & Share Report [2029]," 2022; Wang and Kricka, 2018). A significant proportion of these POC testing solutions stem from research conducted at academic institutions. As part of their third mission to valorize research, universities increasingly rely on academic spin-offs to realize this mission (Compagnucci and Spigarelli, 2020; Hossinger et al., 2020). Yet, many start-ups (up to 90%) (Aminova and Marchi, 2021) and academic spin-offs fail (up to 75%) (Fernández-López et al., 2020; Mustar et al., 2008).

The same trend can be observed for POC technology commercialization through spin-offs. Academic institutions struggle to make the so-called transition from "bench to bedside" as they often lack business expertise and face uncertainty regarding how their solution can create value in the market (Lehoux et al., 2014). In fact, most academic spin-offs fail long before the core technology can be brought to the marketplace because of a mismatch between performance and usability measures of the POC device such as accuracy, cost, complexity, assay stability on the one hand and the needs of the end-users on the other (Weigl et al., 2012).

Existing research on the commercialization of POC testing has mainly focused on the technical challenges lying ahead, concerning both the technical attributes of the biosensors themselves and the scale-up of production. Successful commercialization depends on solving technical issues pertaining to robustness, reliable and fast response, prevention of sensor fouling, and component integration amongst others (e.g., D. Chin et al., 2012; Romanholo et al., 2021). Once these technical hurdles are met, the next challenge concerns the need to scale-up production. Large-scale production can take many year as difficult choices have to be made regarding materials and their structures, processing and assembly techniques; each of which may affect the reliability of the device (R. Reyes et al., 2021). But even if a company succeeds in conquering all

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these technical hurdles, market acceptance is not guaranteed, as the value of a biosensor does not merely depend on technological performance but also on how well the solution matches with customer needs. Indeed, formulating a value proposition that connects the features of the technology to the expectations of customers (e.g. physicians, nurses, patients, third-party payers) to whom value is offered and the expectations of capital investors and shareholders for whom value is captured, constitutes the main challenge in commercializing POC testing solutions (Lehoux et al., 2014; Nayak et al., 2019; Weigl et al., 2012).

The challenge of identifying market domains in which technology features meaningfully meet customer demand by means of a value proposition is in the entrepreneurship literature commonly known as the technology-to-market linking or search for market opportunities problem (Gruber et al., 2008; Helfat and Lieberman, 2002). A large body of literature has investigated the factors that trigger search for market opportunities and its associated outcomes. In particular, this stream of research has studied the usefulness of different strategies to search for *solutions* (Katila and Ahuja, 2002; Maggitti et al., 2013; Lopez-Vega et al., 2016), but has largely neglected the exploration of *problems* (Posen et al., 2018). Yet, adequate problem-exploration is crucial for effective search, because of the irreversibility of the problem-solving process (Volkema, 1983). Especially in entrepreneurial contexts where the value of solutions does not merely depend on technological performance but also on how well the solutions match customer needs, problem-exploration should be an inherent part of the problem-solving search process. While the desired technological performance criteria are known ex ante, the criteria that determine the attractiveness of the solutions on the market are unknown ex ante, thereby necessitating a search of the problem landscape. This search is needed to uncover the nature of the problem and detect the needs and desired preferences of customers and ultimately develop commercially viable solutions.

Taking an entrepreneurship theory perspective, this study investigates how search for problems and solutions contributes to the development of commercially viable biosensors in the context of an innovation contest. The setting of an international healthcare innovation contest offered the opportunity to explore this question, for it is impossible to study search patterns in retrospect, i.e. after the academic spin-off is founded because crucial decisions regarding solution design and targetted customer problems are already taken at that point. The empirical analysis is based on the longitudinal analysis of interim submissions of 11 teams participating in the SensUs 2018 contest. After thematic coding, the data was analysed using methods such as cross-case comparison and within-case comparison over time.

The study results show that the teams differed significantly in *how* they explored the *problem areas*, which in turn led to a large diversity in commercial viability scores (assessed by an independent jury of experts). In particular, this study finds that the teams who adopted search patterns with a ‘broader’ (i.e., considering a wider range of problems and stakeholders) and a more ‘interconnected’ (i.e., thematically linking problem areas with one another) problem-exploration during the contest managed to develop technological solutions with greater commercial potential. Moreover, teams that consulted market experts to explore problems also performed better.

Thereby, this study complements current research on the commercialization of biosensors by underlining the importance of problem-exploration. It demonstrates that the search process of tackling innovation challenges to create commercially viable outcomes involves more than just developing technologically sophisticated solutions, and emphasizes the critical role of exploring the problem landscape.

2. Theoretical backgound: identifying market opportunities

Translating innovative technologies into marketable products requires the development of a business model that operates as a “focusing device that mediates between technology development and economic value creation” (Chesbrough and Rosenbloom, 2002). Central to this process is the identification of market opportunities that meaningfully link technological features and functionalities to customer demands and preferences. Yet, the identification of these market opportunities is far from straightforward as it concerns a prospective and provisional task whereby the demands and preferences of future customers are unknown a priori (Lehoux et al., 2014). However, postponing the identification of market opportunities is not an appropriate strategy as it implies technology developers continue to rely on incorrect or incomplete assumptions. In fact, as a consequence, they may “unknowingly spend the rest of the project attempting to identify and recover from these wrong assumptions” (Martin et al., 2012).

Indeed, ever since Eric Ries launched his book “The Lean Startup” it has become common wisdom that most innovative ventures do not fail because of technological concerns but because they build products customers do not want (Ries, 2011). The lean startup methodology relies on “customer discovery,” a process by which entrepreneurs develop hypotheses about their business models and then validate or invalidate those hypotheses by conducting numerous interviews with potential customers. Doing so, the lean startup methodology aims to reduce waste by eliminating unnecessary research and development. Before developing products or even prototypes, startups should find out if they have actual customers and understand what these customers want. This implies that instead of focusing on building solutions, start-ups should focus on customer discovery entailing the following three questions: “(1) Do customers recognize that they have a problem you are trying to solve? (2) If there was a solution, would they buy it? (3) Would they buy it from us?” (Ries, 2011; Shepherd and Gruber, 2021). Once a thorough understanding of the customers, their needs and preferences is developed, the entrepreneurs can evaluate to what extent their technological invention meets those requirements, if additional technology is needed and start building a prototype to test problem-solution fit.

Yet, how entrepreneurs can best develop an understanding of the problem they aim to solve, it not well understood (De Cock et al., 2020). The process of seeking information to understand what problem to solve can be described as a process of search. According to the literature, search can be conceptualized as the acquisition of new knowledge either through primary (e.g. experimentation) or secondary sources (Sidhu et al., 2007). To structure the search landscape, different search dimensions have been introduced. First, this stream of research has studied the usefulness of different strategies to search for solutions (Katila and Ahuja, 2002; Lopez-Vega et al., 2016; Maggitti et al., 2013), but has largely neglected the exploration of problems (Posen et al., 2018). Next to the nature of knowledge, one should also consider the mechanisms through which the knowledge is acquired. This new knowledge can be acquired internally through experimentation and trial-and-error learning (Andries et al., 2021; Bocken and Snihur, 2020), yet this approach only works for the development of technical knowledge but not for market insights. Alternatively, the organisation can make use of external sources of information such as competitors, suppliers, customers, research institutes, conferences, online communities etc. (Laursen and Salter, 2006).

To provide more guidance to entrepreneurs in general and academics in particular seeking to commercialize biosensors, this paper aims to investigate how different approaches regarding search (i.e. acquisition of knowledge) translate into commercially viable biosensor projects.

3. Methods

To shed light on the search patterns innovators adopt while developing biosensors, a qualitative case study of the SensUs 2018 innovation context was conducted. Qualitative research is particularly suited to study research questions of exploratory, descriptive, or explanatory nature, and is considered as the preferred research method for addressing “how” and “why” questions, when the investigator has little control over events, and the focus is on a contemporary phenomenon within a real-life context (Yin, 2009). Case studies are commonly used in business research (Eisenhardt and Graebner, 2007). While case studies do not aim to generalize to populations (statistical generalisation), they aim to understand the nature of the research problem rather than the quantity of observed characteristics (Baskarada, 2014).

For this study, the SensUs 2018 contest, the third edition of an international student innovation contest organized by professors and students from Eindhoven University of Technology in the Netherlands was selected. For this initiative, 13 teams of engineering students from different universities (nine from Europe, two from North America and one from Asia) competed for four awards (i.e. analytical performance, creativity, translational potential, and public inspiration). The SensUs 2018 contest challenged teams of students to develop innovative biosensing technologies for the biomarker measurement of the antibiotic drug vancomycin (SensUs-2018). To assist the student teams in addressing this innovation challenge, their local institutions provided them access to various resources (e.g. lab space, research facilities, materials), project supervision (by university staff and alumni members), specialized advice (from industry experts), as well as guidance on technicalities/planning (by SensUs members and external consultants) and entrepreneurial issues (by university staff). This competition was selected because it enabled the observation of problem exploration in relation to commercial viability thanks to the set-up of the competition. A more detailed motivation of the case selection can be found in Appendix 1.1.

3.1. Data collection

This study monitored the SensUs 2018 contest from the initial planning phase (i.e. contest organisation, team recruitment and contest instruction) through the development period of the biosensor to the final contest event (i.e. prototype demonstration, pitches, evaluation and award ceremony). From all the data accumulated throughout the contest, the focus was on the search activities of 11 out of 13 participating teams (cases) of exploring problem and solution landscape. Two teams were excluded due to data incompleteness. An overview of the participating teams and their results is available on https://www.sensus.org/archive/2018.

3.2. Data sources

Thanks to a close cooperation of the authors with the SensUs organisation, multiple sources of data were accessible. The SensUs competition offered a richness of data such as project submissions (assignments) and assessment forms (commercial viability assessed by the contest jury), complemented with a range of contest documents, meeting minutes and audio recordings of (Skype) feedback sessions with the participating teams. As part of the entrepreneurship training, the teams were invited to submit interim assignments that assisted the teams to explore the key problems and potential solutions of the predefined innovation challenge next to the final submission. As such, it was possible to observe both an intermediate stage of problem and solution development (i.e. stage 1) and the final version (as submitted for the competition's final event, i.e. stage 2). These submissions along with the final jury assessment forms served as key sources for the in-depth data analysis. Furthermore, other documents (e.g. meeting protocols) and recordings of group sessions delivered additional insights into the teams' problem-exploration when there was a lack of clarity. These sources were used for data triangulation to eliminate ambiguities and to validate preliminary findings and interpretations, and to develop a better understanding of the context within which the teams were operating. A complete overview of the data sources used is available in Appendix 1.2.

3.3. Data coding

To code the rich data, a combination of deductive and inductive coding, i.e., a blended approach was adopted (Graebner et al., 2012). Whereas deductive coding offers structure and theoretical relevance from the start, inductive coding ensures closeness to the data. The basis for the coding procedure is the distinction between problem and solution landscape as suggested by von Hippel and von Krogh (von Hippel and von Krogh, 2015), and thus deductive in nature. Within these overarching categories of problem or solution landscape, inductive coding schemes were developed. The *problem areas* (see Appendix 1.3.) were categorized as covering *the predefined problem descriptions and all problem-related aspects that require the teams' attention in identifying possible solutions*. The *solution areas*, on the other hand, were related to the features and functionalities offered by the biosensing technology solutions. They comprised *all solution approaches that were proposed in response to the identified problems, as well as sources of inspiration for the solutions*. Both problems and solutions were coded at two stages or moments in time (i.e. the intermediate stage 1 and the final stage 2).

3.4. Data analysis

To establish patterns of *how* innovation contest participants navigate the problem and solution landscape and how this affects the commercial viability, cross-case analysis was used. First, the problem and solution search areas of 11 teams were tracked at two moments in time (stage 1 and 2). This enabled a deeper understanding of the search patterns and to what extent problem and solution areas were added, maintained or disregarded. For this purpose, the total number of problem and solution areas considered per team for each stage was counted. Furthermore, the number of stakeholders considered by the teams when discussing certain problem or solution areas was counted. After coding both problem/solution areas and stakeholders, overlaps between coded data (via NVivo analytical tools) were visualized to check whether problem areas were thematically interlinked to other problem or solution areas and stakeholders. In the second step, the actual cross-case analysis, the problem and solution areas were again compared across the 11 cases (teams), after categorizing the cases according to commercial viability scores (awarded by the jury via assessment forms) in four classes: top, good, average and poor performers. The purpose was to examine whether specific search patterns were more or less successful in achieving commercial viability.

4. Results and discussion

4.1. Search patterns development over time

To map *how* the participants navigate the problem and solution landscape, the number of identified problem and solution areas between two interim stages of the contest was compared (summarized in Table 1). In general, it was observed that nearly all teams expand the number of problem and solution areas they consider. This is quite obvious as participants become more aqcuainted with the nature of both the problems and solutions and therefore are able to transform the very generic problem-solution pair of using biosensing technology to measure Vancomycin levels in the blood into a more detailed value proposition. More interestingly though, is the extent to which the teams no longer consider certain problem and solution areas in stage 2. In general, the teams tend to disregard problem areas more easily than they tend to disregard solution areas. Of the eleven teams, seven teams disregarded problem areas, while only four teams disregarded solutions areas. Also the differences across teams is more pronounced when it concerns problem areas (i.e., the number of problem areas disregarded varies from two until five). When teams decided to no longer consider specific solution areas, they typically only abandon one area (Team 1 being an exception with three solution areas that were disregarded). This indicates that during innovation contests, problem landscapes are dynamic and changing as the teams tend to shift and expand their problem formulations, while the solution landscape is more stable and mainly expanded. Althoug the sample is too small and the purpose of qualitative

Table 1
Search patterns regarding problems and solutions per team.

Team	4		5		8		6		10		3		7		11		2		1		9	
Commercial viability	Top		Top		Top		Good		Good		Good		Average		Average		Poor		Poor		Poor	
Stage	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
No. of Problem areas considered	8	14	10	12	7	3	3	7	6	11	3	2	3	6	5	5	0	10	3	3	0	2
No. of Problem areas released		2		3		5		0		2		3		0		3		0		3		0
No. of Problem areas added		8		5		1		4		7		2		3		3		10		3		2
No. of Solution areas considered	5	10	6	9	6	5	5	6	5	11	1	2	3	5	5	5	3	6	4	6	1	2
No. of Solution areas released		0		0		1		0		0		0		0		1		0		3		1
No. of Solution areas added		5		3		0		1		6		1		2		1		3		5		2
Problem space	expand		expand		reduce		expand		expand		reduce		expand		constant		expand		constant		expand	
Solution space	expand		expand		reduce		expand		expand		expand		expand		constant		expand		expand		expand	
HC insurer (dummy)	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
HC professionals (dummy)	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	0	1
Hospitals and labs (dummy)	1	1	1	1	1	1	0	1	1	1	0	1	0	1	0	1	0	1	0	1	0	1
Patients (and their families) (dummy)	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	1	1	1	0	1
Population as a whole (dummy)	0	1	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	1	0	1	0	0
Public health organisations (dummy)	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Types of Stakeholders considered	3	5	3	3	6	3	2	3	4	3	2	2	1	2	3	3	0	5	2	4	0	3
No. of Technical experts consulted		9		2		0		3		3		3		3		8		1		6		7
No. of Market experts consulted		8		6		4		1		5		1		2		0		0		0		0

studies is not to draw statistical interferences, a correlation matrix is available in Appendix 1.4. Confirming the relations as described above.

4.2. Search patterns in relation to contest performance

Next, we engaged in a cross-case analysis to determine how the search patterns affected performance in the innovation contest. In total three search patterns emerged from comparing the varying team performances in the commercial viability assessment (better versus worse ranked teams).

First, the cross-case analysis shows that better teams were clearly engaging in a 'broader' problem-exploration than teams with worse ratings. This was reflected in two search dimensions, i.e. the number of problem areas and the number of stakeholders that were considered in the problem-exploration (Table 1). The best teams demonstrated a higher level in both dimensions. Second, the analysis revealed that better teams performed a more 'interconnected' problem-exploration by thematically linking problem areas with each other (see Fig. 1). Third, teams with a better score on commercial viability consulted more often and to a greater extent market experts rather than technical experts. We elaborate on those three search pattern in the following paragraphs.

4.2.1. 'Broader' problem-exploration through considering a wider range of problem areas and stakeholders

When comparing the problem areas of the three best teams (teams 4, 5, and 8) with the three worst rated teams (teams 2, 1, and 9) at stage 1 and stage 2, we observed that the teams with worse ratings had not yet considered a wider variety of problem areas in stage 1 while the best teams already considered a 'broad' range of problem areas (see ticked boxes in Appendix 1.5.). Because both stages build on each other by deepening or expanding the 'knowledge base' per team, the better teams also take on average more problem areas into consideration in stage 2

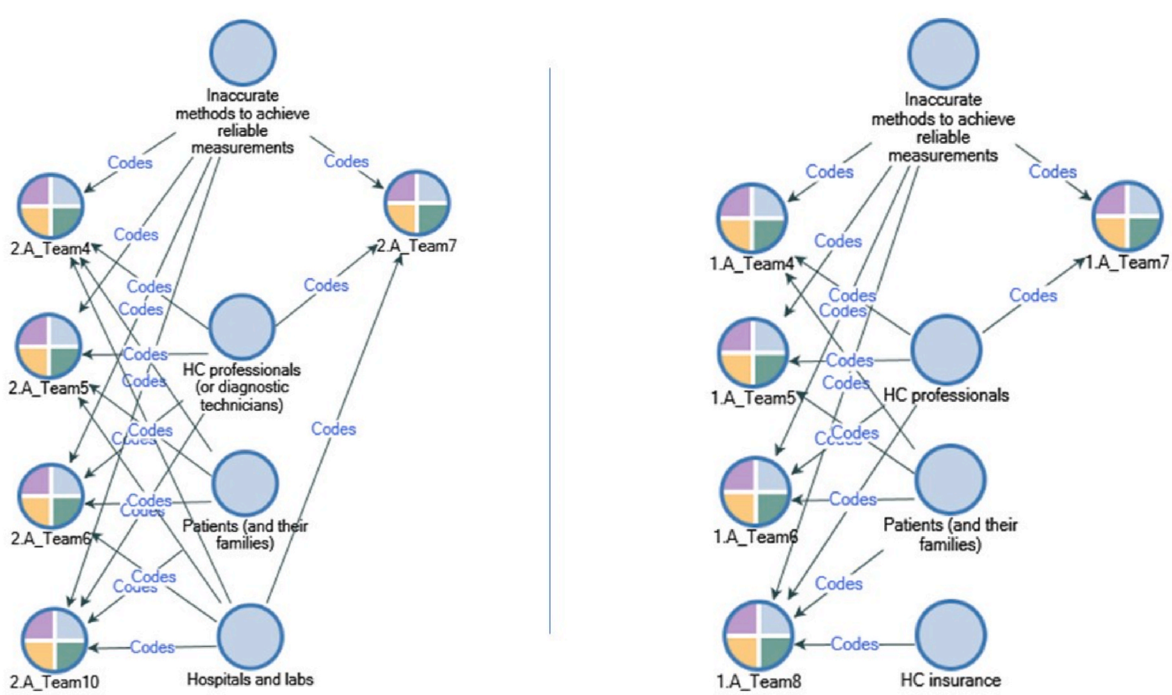

Fig. 1. Comparing stakeholder consideration best performing team for exploring one problem area at stage 1 and 2.

(relative to worse teams). Overall, worse teams start only in stage 2 to consider certain problem areas. Another observation is that the 'broader' problem-exploration adopted by the best teams also implies a relatively dynamic search pattern from stage 1 towards stage 2 (cf. Table 1), that is, teams 4, 5, and 8 engage both in including 'new' problem areas and disregarding 'previously' considered problem areas, unlike worse teams who mainly focus on exploring new problem areas. Not only did the better teams address more problem areas compared to lower ranked teams, they also demonstrate a more thorough level in exploring these problem areas. The coded texts in the dataset confirmed that most of the better teams carried out a rigorous problem analysis, while lower ranked teams showed a tendency towards conducting only the basic steps in the analysis (e.g. describing problems without validating the underlying assumptions).

The data analysis further demonstrated that exploring a particular problem area from the angle of more than just one stakeholder (e.g. healthcare professionals and patients) improved the commercial viability of the developed solutions. In Fig. 1 we see that teams with better ratings on the left (e.g. teams 4, 5, 8, 6, 10) took on average two or more stakeholders into consideration, whereas a team with worse rating (e.g. team 7) did only consider one or two stakeholders, respectively, and all other teams with worse ranked teams on the right (teams 11, 1, 2, 9) did not make any reference to stakeholders in the coded data. In other words, better teams tried to get to the bottom of the problems by evaluating how the problems influence (or are influenced by) various stakeholders while worse ranked teams were addressing the problems primarily in the light of the main customer group (i.e., only healthcare professionals or patients). Even though most teams arrived at considering more than just one stakeholder in stage 2, the worse ranked teams still limited themselves to the three key stakeholder groups (i.e., healthcare professionals, patients, hospitals/labs) who directly interact with the final technological solutions. Not including stakeholders outside these three groups (e.g. pharma/diagnostic companies, health insurance, NGOs, governmental and public health institutions, etc.) may offer only a limited view on the potential market when aiming for commercially viable solutions.

4.2.2. *More 'interconnected' problem-exploration by linking multiple problem areas*

Secondly, we observed that the teams differed in how they were able to interconnect problem areas in a broader problem context. Fig. 2 illustrates this difference between better and worse ranked teams by comparing two problem areas in the project map (software NVivo). It visualizes the link between two problem areas which exemplifies how mostly better teams (highlighted in bold) managed to establish this connection in their problem-exploration.

To further verify this finding, we investigated whether individual problem areas were closely linked with other problem areas, which means that they were coded in the same sentences or text segment (within close proximity). For this purpose, we picked problem areas which were addressed by all participating teams to equally compare differences across teams (results available in Appendix 1.6.). This table visualizes how one particular problem area (highlighted in the middle) was thematically closely interconnected with surrounding problem areas (boxes marked with "X"). For instance, some of the better teams (4, 5, and 10) had at least five linkages with other problem areas, as opposed to teams with worse ratings (columns on the right: teams 1, 2, 7, 9, 11) who showed either no linkages or very few. This finding underlines that teams who performed better on the translational potential (i.e., the commercial value of the developed solutions) were also able to better explain and connect the problem areas, thereby putting them into a broader context. This deeper understanding of how one problem area may infuence or relate to other problem areas, and vice versa, provided a more comprehensive picture of the whole problem context. Hence, the deepened knowledge of these links or pathways proved to be essential for developing commercially viable solutions.

Fig. 2. Overview of teams that connected two problem areas versus teams that only considered one problem area.

4.2.3. *Consultation of market experts*

The third result relates to the channels of information search that were used by the participants. In particular, we checked what type of advice and feedback the participants sought. Table 1 illustrates that the more successful teams tend to rely on more sources and pay more attention to market feedback. By interacting directly with the different actors or stakeholders involved, they were able to gather insights that are otherwise unavailable and contributed to a deeper and more meaningful understanding of the problems of potential customers. The less successful teams on the other hand preferred to ask feedback from technical experts and thus were concentrating mainly on the technical challenges without considering how a biosensor could address the needs, problems and preferences of the customers. This is also apparent from the correlation matrix that can be found in Appendix 1.4.

5. Discussion

This study's empirical observations indicate that developing a commercially viable biosensor involves a search process of exploring the problems and evaluating them based on the growing knowledge base. In this regard, the findings illustrate that exploring problem areas more 'broadly' to capture a more comprehensive picture of the problem context, is a fundamental part in developing commercially viable solutions. This is in line with previous research on design processes which also underlines the importance of problem-exploration. Firstly, the iterative process of refining or 'reframing' the problem(s) by understanding all underlying problem aspects is key to creative problem-solving (Dorst and Cross, 2001). Secondly, the expansion of the 'problem-frame' enables to explore the problem(s) from many different standpoints and thereby may provide a larger variety of solutions. A problem-solving approach which focuses on problem-exploration is also supported by research on design processes (Kruger and Cross, 2006), where designers who employed a problem-driven strategy achieved outcomes with better overall quality scores than those following a solution-driven strategy. In this regard, patient care pathways provide a useful concept for healthcare innovations to explore customer problems and detect bottlenecks and opportunities for improvement by analyzing the situation as-is (Williams and Radnor, 2018), while BPMN (Business

Process Model and Notation) provides a useful modeling tool to do so (Pufahl et al., 2022).

Secondly, the findings stress the importance of considering a 'broader' set of stakeholders during problem-exploration to develop commercially viable solutions. The crucial role of a multi-stakeholder involvement is also discussed by previous studies on knowledge and value co-creation (Reypens et al., 2016). In order to create valuable knowledge for developing innovative solutions to complex challenges, firms consider multiple external sources (i.e., different types of stakeholders) to learn and develop new capacities for addressing the market's ever-changing needs. Indeed, the search for commercially viable solutions presents a complex innovation challenge due to conflicting interests, strict regulations, and high competition on the healthcare market. Hence, acquiring a deeper understanding of the current problem situation, and how problems mutually influence each other, is necessary for problem-solving in a complex network of healthcare actors.

6. Conclusions

To summarize, this study demonstrates that for effective problem exploration leading to commercially viable POC biosensors, it is important to take a broad perspective by considering different dimensions of the problem, seek connections between those different elements and rely on primary data sources (i.e. direct interviews with actors from the field) that have in-depth knowledge and first-hand experience with the problem you aim to solve. This study was conducted in the context of a biosensor innovation contest. Case studies aim to understand phenomena, but are not suited to generalize the findings to a broader population. Therefore, further research is needed to confirm whether these results hold for other (non-student) teams developing biosensors and in the context of actual start-ups, rather than the early phases preceding a potential start-up.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bios.2023.115636.

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