MASTER

# Overcoming the social barriers of AI adoption

Bianco, Martina

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# Overcoming the social barriers of AI adoption

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Martina Bianco

Student identity number: 1442864

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*TU/e Supervisors:*

First Supervisor: dr. J. Bonnin Roca

Second Supervisor: prof. dr. ir. I.M.M.J. Reymen

Third Supervisor: dr. Jan A. Millemann

*Company Supervisor:*

drs. C.B. Admiraal

# Executive summary

Artificial Intelligence (AI) is a promising technology that leads to significant benefits such as increase efficiency or competitive advantage. However, it poses also compelling obstacles. On the one hand, AI developers are exploiting its business opportunities, on the other hand, customers and public institutions are cautious in taking any kind of decision (Dwivedi et al., 2021; Canhoto & Clear, 2020). This technology indeed is facing considerable social resistance caused by several factors. It is in this scenario that the AI Innovation Centre (AIIC) envisioned itself and the industrialization of AI within the Brainport Eindhoven region. The AIIC is located within the High-Tech Campus' ecosystem (HTC) and it was founded in collaboration with four other key players, namely Philips, ASML, NXP and Signify. The Centre positioned itself as a facilitator through three strategic milestones: (i) providing an AI ecosystem & infrastructure, (ii) accelerating AI projects and applications, and (iii) hosting AI events & education (AI Innovation Centre, 2021a). Concerning the second and third goals, the AIIC does not have a clear strategy on how to best approach them. However, the Centre presents an advantageous position that allows an "inter partes" role between customers and AI developers making customer education easier to implement. Therefore, the question leading the study is: "*How can the AI Innovation Centre help accelerate AI technology projects by providing customers access to technical skills and information to overcome their social barriers?*"

In the first part of this study, I selected drivers and obstacles to technology acceptance. To do so, I first identified the TAM as the most suitable model to represent AI acceptance and described the drivers *perceived ease to use* and *perceived usefulness*. Second, I analyzed the most common social barriers to technology adoption identified in the literature. This led to the initial screening of six social barriers, namely *customer awareness*, *access to technical skills*, *lack of trust*, *safety*, *security*, and *job displacement.* Third, I applied the TAM to the obstacles selected and analyzed the positive impact of *customer awareness* and *access to technical skills*. Next to this, I described the negative impact of *lack of trust*, *safety*, *security*, and *job displacement* highlighting how the first affects the impact of the others. Lastly, I explored best practices for awareness creation and facilitating access to technical skills. This was essential to design an approach for the AIIC that could accelerate AI adoption and counteract the negative effect of the other four barriers.

The second part of my investigation consisted of a qualitative analysis to validate the model proposed and establish the content of the designed solutions. This study collected the experience of eight AI developers operating in healthcare or smart manufacturing industries. In addition, ten potential customers shared their experiences and allowed this study to reach insightful results. I defined potential customers as any company that could potentially apply AI but has it not yet. The results of the interviews suggest the presence of the six social barriers previously selected. Besides, *internal support* and *social pressure* were also considered as obstacles. Next to this, findings highlight the dissonance between AI developers and potential customers in terms of expectations towards the technology, fundamental knowledge, and access to technical skills. However, as regards to technical skills, their identification was not possible since interviewees were confused

about the definition of “skills”. Nonetheless, AI developers identified twelve qualifications that would facilitate AI adoption.

In light of these results, I designed two solutions that answer the research question. First, the AI qualification framework visualizes the twelve qualifications resulting from the interviews, their definition, level of expertise required, and any difficulty in accessing those profiles. This tool guides the AIIC in its role of facilitator in accessing technical skills. Moreover, the framework also helps potential customers in selecting themselves their human capital shortfalls. Second, the Customer Awareness Program (CAP) is a collection of workshops that provides to potential customers fundamental information about the technology, use cases, and contacts within the Region. In this way, customers interact with the technology and overcome initial distrust. Moreover, the Program encourages self-mobilization and knowledge sharing, stimulating not only *customer awareness* but also *social pressure* and *internal support*.

Furthermore, I organized a focus group to collect feedback from the AIIC team concerning whether the AIIC can integrate the solutions suggested, their effective use, and the resources necessary to provide them. The insights were implemented into the two solutions. Besides, a last iteration with the team concluded the feedback process. Lastly, I identified the theoretical contributions of this investigation as well as its managerial recommendations, limitations, and future research suggestions.

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# Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| AIIC | AI Innovation Centre |
| HTC | High Tech Campus |
| DOI | Diffusion of Innovation theory |
| SCT | Social Cognitive Theory |
| TAM | Technology Acceptance Model |
| TPB | Theory of Planned Behavior |
| UTAUT | Unified Theory of Acceptance and Use of Technology |
| SME | Small and Medium Enterprises |
| JIF | Journal Impact Factor |
| EQF | European Qualification Framework |
| CAP | Customer Awareness Program |
| KPI | Key Performance Indicator |

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# 1. Introduction

AI technology brings several benefits, such as a reduction in human errors or improvements in quality of life, which are potentially disruptive both for companies and society (Dwivedi et al., 2021; Duan, Edwards, & Dwivedi, 2019). However, this radical innovation is controversial because it also entails compelling challenges, such as judicial transparency or security vulnerability. In this matter, there is a schism of public opinion: AI developers are capitalizing on business opportunities, but customers and public institutions are still considering whether the technology is more beneficial than risky (Dwivedi et al., 2021; Canhoto & Clear, 2020). Therefore, one of the strongest obstacles to AI adoption is the social opposition to the technology. However, numerous studies prioritize the economic and technological aspects of AI, overlooking this critical element (Pan, 2016).

These social constraints, if channelled correctly, may become a powerful driving force to adoption (Pan, 2016). Customer awareness and skilled human capital are two examples of social barriers that, if stimulated in the right direction, can foster adoption (Brock & Wangenheim, 2019; Stix, 2018). Particularly in the AI landscape, where ethical debates are ongoing, stakeholders involved in the technology must be well informed of both the benefits and drawbacks. This is important to implement the technology successfully and avoid "surprises" once the process is initiated. However, being informed is important but not sufficient to adopt the technology. For a successful adoption, companies must engage in a broad-based investment combining technical implementation with human capital investments (Barro & Davenport, 2019). However, the search for AI-related skills (i.e., advanced data science, cybersecurity) might result as more difficult than predicted. Therefore, to encourage AI acceptance and relative adoption, AI developers should inform their customers and facilitate their access to expertise. Nonetheless, AI developers cannot engage in these practices for two reasons. First, informing customers might provide them with the necessary information to switch to the competition (Bell, Auh & Eisingerich, 2017). Second, the shortage in AI expertise does not allow them to have more access than the customers potentially have or to share their internal resources.

It is in this context that the AI Innovation Centre (AIIC) has positioned itself to promote AI awareness and access to skilled human capital. The AIIC is located in Eindhoven, the Netherlands, within the High-Tech Campus ecosystem (HTC). The HTC is an active (and key) player to foster high-tech technology in the Brainport Eindhoven region. This ecosystem uses "proximity" to stimulate interactions and innovation among its members (Van der Borgh, Cloodt, & Romme, 2012). All the parties involved in the ecosystem are also residents of the campus. Philips established HTC in 1998, and in 2003, its mission of being an open innovation ecosystem enabled the incorporation of companies from all over the world. HTC is one of the main (and most active) partners of AIIC together with Philips, ASML, NXP and Signify. AIIC was founded to stimulate the industrialization of AI within the Brainport Eindhoven region. However, the AIIC ecosystem is relatively new, and it does not know how exactly to achieve its ambitious goals.

## 1.1 Company context

At the beginning of 2020, HTC redefined its strategy for the upcoming ten years. In its investigation, HTC asked all its residents their future expectations and which technologies were essential to remain competitive in the high-tech industry (High Tech Campus, 2020). AI technology was one of the most requested domains. Therefore, HTC in collaboration with other four partners (i.e., Philips, ASML, NXP and Signify) founded the AI Innovation Center (AIIC). The goal of the five founders was to create a regional AI ecosystem that allows all partners to stay ahead of the high-tech industry trends and create business opportunities within the ecosystem. The vision of the AIIC is to industrialize AI within the Brainport Eindhoven region through three action lines: (i) providing an AI ecosystem & infrastructure, (ii) accelerating AI projects and applications and (iii) hosting AI events & education (AI Innovation Centre, 2021a). Nonetheless, the AIIC lacks a clear action plan to bridge the gap between AI developers and potential customers.

However, the AIIC dedicated its first efforts in creating a community of AI enthusiasts around the Centre. This community is divided into seven circles which focuses on specific aspects of the technology, namely *(1) AI for good*, (2) *deep learning*, *(3) machine learning, (4) digital transformation, (5) ethics*, *(6) legal* and *(7) sports.* Each circle has several members who are either directly working for companies developing AI solutions, independent professionals, or AI enthusiasts. Thus, the resources and network that AIIC has access through its community, are key to develop its vision.

Furthermore, the partners that initially founded AIIC also contribute to the Centre's effort of industrializing AI in the Region. First, HTC is an ecosystem built around high-tech technologies that involve over 10.000 people with more than 50 companies that are residents of the campus (Van der Borgh, Cloodt, & Romme, 2012). HTC contributes through its innovation community with easy access to skilled human capital and potential customers. Second, the other four partners, namely Philips, ASML, NXP, and Signify, are the most technologically advanced companies that are residents of the campus, with access to significant financial investments, deep knowledge of high-tech markets, and human capital. These partners are a golden opportunity for startups, SMEs, and other AI developers. As a result, AIIC is appealing from the outside due to its access to professional human capital as well as the services and opportunities provided by its network.

## 1.2 Problem statement

The goal of a tech-based firm is to know why customers adopt (or do not) the technology and leverage those drivers to cross the "chasm". However, there are different variables and other contextual influences that come in between the customer's perception of the technology and subsequent decision to adopt.

In this scenario the AIIC wants to accelerate AI projects in the region, but its action is limited in certain areas: the Centre does not have any decision power over financial or technical matters. Nonetheless, this position entrusts the AIIC as an "inter partes" player allowing it to be the bridge between AI developers and customers. However, the Centre has not a clear plan on how to leverage this role and accelerate AI projects. Therefore, the problem statement is formulated as follow:

*AI Innovation Centre wants to stimulate the acceleration of AI projects in the Brainport Eindhoven region, but the Centre lacks a clear approach to achieve its goal.*

## 1.3 Research Question and Sub-questions

AI technology is controversial and its future development lines raised scepticism around the technology (Dwivedi et al. 2021; Kaplan & Haenlein, 2019). This resistance is defined by Cubric (2020) as technical barriers, economic barriers, and social barriers. According to the resources and vision of the AIIC, the Centre can significantly contribute to encourage knowledge sharing and access to skill human capital. Both factors are crucial to overcome the social barriers to AI adoption.

Therefore, the research question that drives this investigation is:

*How can the AI Innovation Centre help accelerate AI technology projects by providing customers access to technical skills and information to overcome their social barriers?*

In this study, "customer" refers to any company who can potentially adopt AI-based solutions. In order to answer to the research question, sub-questions are identified and organized in three clusters: literature review, qualitative analysis, and design solutions. Regarding the first cluster, I conducted a literature review, presented in chapter 3, to build a theoretical foundation on the research topic:

1) *Which are the drivers and social barriers to technology adoption recognized in the literature and how do these apply to AI?*
2) *Which are the best-practices to stimulate awareness and access to technical skills recognised by the literature?*

Relatively to the second cluster, I validated what stated in the literature concerning the social barriers to AI adoption. Next to this, I identified key qualifications that customers can access to facilitate AI adoption and their relative knowledge gaps in relation to this technology. The questions comprised in this cluster:

3) *Which are the most common social barriers to AI adoption identified among AI developers? And which are the common technical skills required for AI implementation across industries?*
4) *Where does the customers' lack of knowledge and access to technical skills stand in relation to AI technology?*

I answer question three in section 6.1, and question four finds resolution in sections 5.1.1 and 5.1.2. Lastly, I designed an AI qualification framework and a Customer Awareness Program (CAP) which aim at supporting AIIC in its vision of industrializing AI through education. This cluster comprises one question:

5) *What can AIIC do to accelerate AI projects in relation to customer education?*

Therefore, I answered to the last sub-question in sections 6.2, 6.3, and chapter 7.

# 2. Industrial context of AI

There is no consolidated description of what exactly "Artificial Intelligence" entails (Dwivedi et al. 2021; Duan et al. 2019; Brock, & Wangenheim, 2019). Artificial Intelligence first appeared in 1950 and has evolved significantly until then (Desouza, Dawson, & Chenok, 2020). In 1955, McCarthy et al. (1955) defined AI as *"making a machine behave in ways that would be called intelligent if a human were so behaving"*. Almost ten years later, Minsky (1968) referred to AI as *"the science of making machines do things that would require intelligence if done by men"* (Minsky, 1968). However, at the beginning of the 2000s the interpretation of AI shifted from acting based on pre-existing knowledge to "conscious machines", meaning AI systems are capable of learning from experience and interact with humans (Bawack et al., 2021). However, the definition provided by Kaplan & Haenlein (2019) is referred more frequently. As a result, in this study, I refer to AI as a "*system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*" (Kaplan & Haenlein, 2019, p. 15). Based on this interpretation, many authors offered similar but different definitions of AI as presented in Table 1.

| Authors | Definition of AI |
|---|---|
| Duan, Edwards, & Dwivedi (2019) | "*It is normally referred to as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks" (p.63).* |
| Kaplan & Haenlein (2019) | *"system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 15).* |
| Grover, Kar, & Dwivedi (2020) | *"AI had been defined as the system's ability to interpret and learn from the digital traces" (p. 2).* |
| Canhoto, & Clear (2020) | *"We define AI as an assemblage of technological components that collect, process, and act on data in ways that simulate human intelligence. Like humans, AI solutions can apply rules, learn over time through the acquisition of new data and in- formation (i.e., via ML), and adapt to changes in their environment" (p. 184).* |
| Dwivedi et al. (2021) | *"systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving" (p. 2).* |
| Raisch, & Krakowski (2021) | *"Artificial intelligence (AI) refers to machines performing cognitive functions that are usually associated with human minds, such as learning, interacting, and problem solving" (p. 192).* |

*Table 1: The different definitions of AI provided by several authors.*

There are some common benefits that customers can enjoy regardless of the specific application of AI. First, the company achieves better efficiency by reducing the error-rate in its business processes and reaching the so-called "Hyperautomation" (Arun, Cearley, & Alaybeyi, 2020; Raisch & Krakowski, 2021). Besides, the technology enables devices such as drones and cars to function autonomously (Arun et al., 2020). Second, by enhancing data analysis, AI can better predict future patterns, support decision-making processes, and uncover new business opportunities (Paris et al., 2017). Therefore, this technology while coping with complexity, it fosters human intuition (Jarrahi, 2018). Gartner identified several development trends in which AI can evolve into in the next few years (Arun et al., 2020). However, the acceptance and adoption of AI does not follow the same path (Bawack et al., 2021; Brock & Wangenheim, 2019).

It is important to also consider the industry of application and the geographic area. Industries differ in terms of complexity, expertise, legislation, or ethical implications (Brock & Wangenheim, 2019; Hengstler et al., 2016). Conversely, developing AI products in America or Asia can be significantly different from Europe (Dwivedi et al., 2021; Kaplan & Haenlein, 2019). Therefore, before exploring social barriers and how to stimulate customer awareness and access to technical skills, it is important to analyse the *context of application* from an industry and geographical perspective.

## 2.1 Context of application - AI application industries

In the past ten years, AI technology appeared in several industries, but its adoption rate differs quite significantly as their applications (Bawack et al., 2021; Paris et al., 2017; Hengstler, Enkel, & Duelli 2016).

- *Healthcare* - e.g., prediction of diseases or high-risk patients' groups, adaptive diagnosis and therapies, optimization of the hospital's operations, cost optimization.
- *Education* – e.g., anticipating market trends, detecting disengagement from students and staff, automating teachers' routine work, build personalize learning environment.
- *Internet services, retailing, marketing, sales and advertising* – e.g., anticipating market trends, warehouses automation, profiling of customers and preferences.
- *Financial services* - e.g., automated traders, opportunity detectors (Alvim, & Milidiú, 2013), improvement of risk selection processes in insurance firms, tailoring of products to customer's risk profile (Baecke, & Bocca, 2017), optimization of fraud detection systems and prevention.
- *IT and telecommunications* - e.g., churn prediction (Coussement, Lessmann, & Verstraeten, 2016), improvement of Web performance (Ali, Shamsuddin, & Ismail, 2012).
- *Transportation, automotive and logistic* – e.g., advanced robotics for manufacturing optimization, anticipating market trends, autonomous driving, detecting anomalous behavior in flight trajectories, plan diversions (Ciccio et al., 2016).
- *Travel and tourism* - e.g., tour recommendations, profiling of customers' preferences, dynamic pricing, workforce management.
- *Energy and utilities* – e.g., enhancing demand and supply, preventive maintenance optimization, optimizing pricing with dynamic tariffing.

High-Tech industries, telecommunication and financial services are the "driving–forces" of AI with the highest adoption rate (Paris et al., 2017). However, healthcare and transportation, for example, face more severe implications in the development and implementation of AI since they directly risk people's lives (Fan et al., 2020; Hengstler et al., 2016). In a study of the adoption of intelligent-based medical diagnosis support systems, Fan et al. (2020) showed that "*before adopting a new product, healthcare professionals should trust the target products with a higher level compared to other individuals*" (p. 589). The authors identified a lack of trained skills and technical knowledge on the new technology as potential explanations (Fan et al., 2020). Therefore, the severity of the social barriers can vary depending on the industry of application.

## 2.2 Context of application – geographic area

The geographical area in which the firm is based influences how quickly AI technology is accepted and adopted. Several factors play a relevant role, such as cultural resistance, lack of talents, lack of data availability and subsidies (JRC Technical Reports, 2018). Over the last two years, the EU Commission and Parliament have instructed multiple inquiries to examine: (i) the opportunities that AI unlocks both for society and economy, (ii) the strongest worldwide players and (iii) the EU position in this context.

Europe have different regulations and public initiatives compared to USA and China, which makes the continent as the third market leader (JRC Technical Reports, 2018). On one hand, the EU Commission launched R&I programme funding to overcome the lack of venture capital in EU (Eager et al., 2020). Next to this, in 2020, Europe committed to an increase of the total investments in AI to €20 billion every year (European Commision, n.d.). On the other hand, there are many open questions on whether this technology is beneficial or completely disruptive to societies' structure (Kaplan and Haenlein, 2019; Paschen, Pitt, & Kietzmann, 2020). In this regard, EU already stepped forward with the recent General Data Protection Regulation (GDPR). The GDPR introduces several limitations and actions that companies must follow to preserve users' privacy. In 2021, as a follow-up on the GDPR, the EU Commission committed its efforts to build trust towards AI by introducing a horizontal regulatory proposal (European Commission, 2020). However, in doing so, EU stepped back from becoming the first market leader in AI development (Kaplan & Haenlein, 2019).

In contrast, while GDPR restricts AI development, it increases consumer trust and security. Structural assurance defined as the institutional environment surrounding the technology adoption (Luo et al., 2019), plays a key role in decreasing risks' perceptions. Therefore, institutional initiatives contribute to mitigate the effect of social barriers on the intentions to use the technology. Next to this, the European countries vary across academic ecosystem, industrial ecosystem, governmental initiatives, and funding ecosystem (Stix, 2018). These factors, in addition to European initiatives, contribute to mitigate the impact of barriers to AI adoption at a European and national scale.

# 3. Literature review

The literature review in this study has two key objectives: identify which are the drivers and social barriers to AI adoption and comprehend how customer awareness and access to technical skills can be the leverage points in overcoming such barriers. As a result, I identified the most used technology adoption theories before selecting the most appropriate one (section 3.1). Once I selected the model, I examined the social barriers of AI adoption and how the framework applies to them (section 3.2). Next to this, in section 3.3, I investigated effective practices to stimulate access to technical skills and customer awareness, considered the leverage points for AI adoption.

## 3.1 Main theories of technology adoption

Multiple technology adoption theories are available in the literature. However, as mentioned by Sohn & Kwon (2020), "*Technology acceptance theory is currently without an objective consensus on which model performs best in each field.*" (p.2). Therefore, after examining different frameworks, I selected upon which best reflects the research question of this study. The frameworks considered are the Diffusion of Innovation theory (DOI), Social Cognitive Theory (SCT), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), the extension of the TAM (TAM2), Unified Theory of Acceptance and Use of Technology (UTAUT) and some proposals of trust-based models.

### *3.1.1 Diffusion of innovations theory (DOI)*

The Diffusion of Innovations theory (DOI) proposed by Rogers (2010) originated from a sociological perspective which considers economics of innovation (Hall, 2004). Because of its roots, the framework has the distinct trait of examining adoption as a collective rather than an individual process (Straub, 2009; Lai, 2017; Roca & O'Sullivan, 2020). This model, in fact, describes adoption in social systems in which one individual's action influences another (Rogers, 2010; Hall, 2004; Lai, 2017). The author describes four components that affect the diffusion of technology which are innovation, communication channels, social system and time (Rogers, 2010; Straub, 2009). Next to this, five factors contribute to the effect of the innovation component:

- *Relative advantage* is the comparison between benefits of the new technology and advantages of the old one (Straub, 2009). If negative, the customer will not adopt.
- *Compatibility* of the past understanding and the new values (Straub, 2009).
- *Complexity* expressed as the degree to which a customer finds it difficult to understand or use the technology (Straub, 2009).
- *Trialability* is the possibility for a customer to try the technology (Straub, 2009).
- *Observability* relates to network effect in the sense that the innovation becomes omnipresent in the customer's reality and those who did not consider adoption at first, will decide differently (Straub, 2009).

DOI is considered one of the most common frameworks to study technology adoption in the field of information management (Taherdoost, 2018). However, there are other areas in which it is applied such as manufacturing-enabling technologies (Roca, & O'Sullivan, 2020), smart homes (Balta-Ozkan et al., 2013) or connected autonomous vehicles (Talebian & Mishra, 2018). Within the study's objectives, DOI includes many social dimensions of technology adoption as relative advantage, compatibility and complexity. In the absence of a common understanding of the technology, which is encouraged by customer knowledge and access to expertise, these factors contribute to customer reluctance to accept the solution. As a result, DOI is a relevant candidate for this research.

### *3.1.2 Social Cognitive Theory (SCT)*

The Social Cognitive Theory emerged from social psychology and socially orientated technology acceptance studies (Sepasgozar et al., 2019; Taherdoost, 2018). As a result, this framework suggests a deep understanding of the social influences that affect a person's behaviour (Straub, 2009). SCT includes the reciprocal synergies between the environment, the person's cognitive perceptions, and the final behavior (Taherdoost, 2018; Compeau et al., 1999). In this model, there are two constructs that describe the cognitive perceptions of a person (Compeau et al., 1999; Straub, 2009; Bandura, 2001):

- *Computer self-efficacy* is a personal assessment of one's own capabilities of completing technology tasks.
- *Outcome expectations (personal)* are the beliefs of status or image change.

Next to this, the customers' final behavior can be either an emotional response or an action and it is determined by four other factors (Compeau et al., 1999; Straub, 2009; Bandura, 2001):

- *Affect* is the positive emotional response of enjoyment or excitement from using a technology.
- *Anxiety* is the negative emotional response of apprehension and uncertainty from using a technology.
- *Usage* is the actual adoption of the technology.
- *Outcome expectations (performance)* are the assumptions of a person that by using the technology her performance will improve.

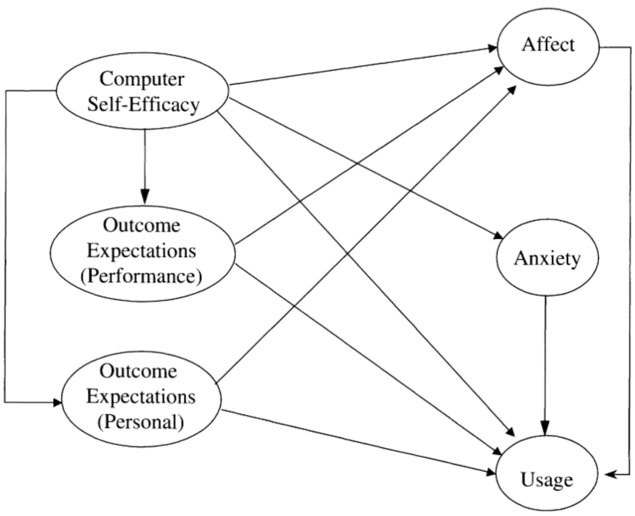


*Figure 1: The Social Cognitive Theory proposed by Compeau et al. (1999) identifies five factors influencing customer's adoption, namely computer self-efficacy, outcome expectations (performance), outcome expectations (personal), affect, anxiety and usage.*

Self-efficacy is key in the SCT because it determines an individual's belief in her own ability to complete specific tasks (Straub, 2009; Bandura, 2001). Self-efficacy is the only construct that directly influences all the others (Figure 1). In this study, this determinant of the final behaviour is especially important for different reasons. First, if the customer has the necessary expertise to use the technology but is unable to complete specific tasks, the innovation will be rejected. Second, if she has the skills but does not know how to apply them due to a lack of technology understanding, the adoption will not occur.

### *3.1.3 Technology Acceptance Model (TAM)*

The Technology Acceptance Model proposed by Davis (1989) builds up on the social psychology Theory of Reasoned Action (TRA), contributing significantly to technology acceptance studies (Venkatesh et al., 2007). However, as mentioned by Compeau et al. (1999) "*TAM (...) focuses almost exclusively on beliefs about the technology and the outcome of using it"* (p. 146) while SCT includes other environmental and personal beliefs. The model suggests that *perceived usefulness* and *perceived ease of use* influence customers' *intentions to use* and subsequent *usage behavior*. Therefore, the factors influencing customer's adoption in the TAM are (Sepasgozar et al., 2019; Marangunić & Granić, 2015; Davis, 1989):

- *Perceived usefulness* is defined as the extent to which people perceive that the technology supports better performance.
- *Perceived ease of use* which partially includes the pivotal role of self-efficacy, is defined as "*the degree to which a person believes that using a particular system would be free of effort"* (Davis, 1989, p. 320).
- *Intention to use* is the predisposition of a person to engage in a particular behavior.
- *Actual usage system* is the actual adoption of the technology.

Several authors suggested extensions to the TAM's implementation as shown in Figure 2 (Marangunić & Granić, 2015) among which:

1. *External predictors* are determinants that directly influence *perceived usefulness* and *perceived ease of use.*
2. *Factors from other theories* are constructs identified in other technology acceptance theory which increase TAM's predictive validity.
3. *Contextual factors* are determinant that could have a moderating effect on the variables of the model.
4. *Usage measures* are operational measures to assess the actual system usage.

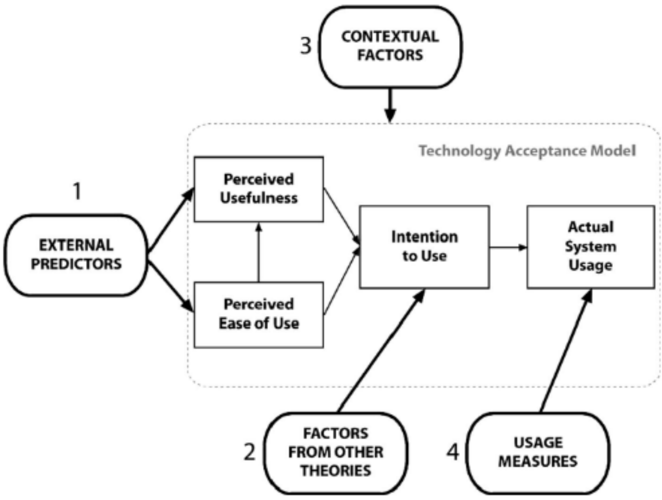


*Figure 2: The Technology Acceptance Model proposed by Davis (1989) withstood numerous extensions among which the addition of external predictors, contextual factors, factors from other theories and different usage measures (Marangunić & Granić, 2015).*

TAM has already been used to explain the adoption of intelligent products such as applications in self-driving cars (Sepasgozar et al., 2019), intelligent healthcare systems (Chen et al., 2017; Pai & Huang, 2011), intelligent learning environment (Sánchez-Prieto et al., 2020). This model is particularly relevant because the predictors of users' intentions partially combine social aspects of SCT and DOI. Perceived ease of use recalls self-efficacy and complexity (Davis, 1989). An individual perceives technology as difficult to use or to understand based, among other factors, on her capabilities to interact with the solution (Davis, 1989). In turn, perceived usefulness partially includes outcome expectations (performance) and relative advantage. Perceived ease of use is facilitated if the person is sufficiently skilled to perform the job. On the other hand, perceived usefulness is encouraged if that person is also aware of the technology's benefits and limitations.

### *3.1.4 Theory of Planned Behavior*

The Theory of Planned Behavior (TPB) is often compared with the TAM as a potential alternative. Both theories originated from the TRA (Lai, 2017; Taherdoost, 2018), but TPB introduces a new determinant of customer's intentions and behavior, namely *Perceived Behavioural Control* (Venkatesh et al., 2003). Next to this, the model integrated other two factors of intentions as shown in figure 3 (Ajzen, 1991):

- *Attitude toward the behavior* is defined as the customer's positive or negative assessment of the task.
- *Subjective norm* is the social pressure perceived by the customer to comply.
- *Perceived behavioral control* is defined as "*people's perception of the ease or difficulty of performing the behavior of interest*" (p. 183).

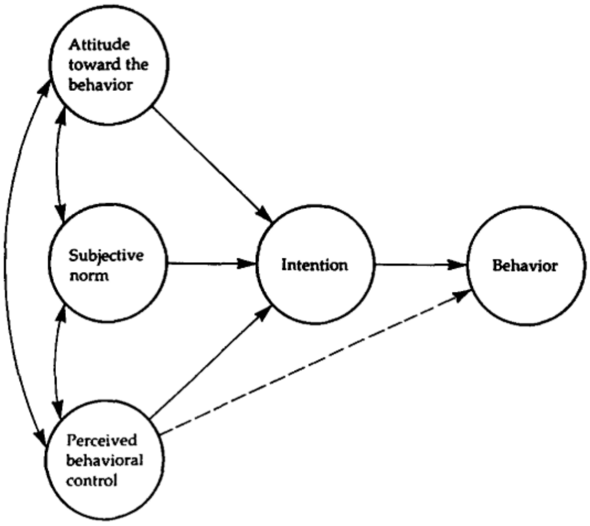


*Figure 3: The Theory of Planned Behavior proposed by Ajzen (1991) introduces a new factor called perceived behavioural control together with attitude toward the behavior and subjective norm. These three elements determine the intentions and the behavior of a customer.*

TPB raises an interesting point when it comes to individual perceptions, specifically perceived behavioural control. As perceived ease of use in the TAM, the difficulty of using the technology can trigger resistance among customers, causing adoption to fail.

### *3.1.5 Extension of the Technology Acceptance Model (TAM 2)*

Inspired by the TPB and the TAM, Venkatesh and Davis (2000) proposed a revisitation of the last one, called TAM2 (Figure 4). In this framework, two processes influence the TAM system: social influence processes and cognitive instrumental processes. The first group introduces the following determinants (Ajzen, 1991; Venkatesh & Davis, 2000; Marangunić & Granić, 2015):

- *Subjective norm* is the social pressure perceived by the customer to comply.
- *Image* is "*the degree to which use of an innovation is perceived to enhance one's... status in one's social system*" (Venkatesh & Davis, 2000, p.189).
- *Voluntariness* is the degree to which customers consider the technology as non-mandatory.

On the other hand, cognitive instrumental processes are (Ajzen, 1991; Venkatesh & Davis, 2000; Marangunić & Granić, 2015):

- *Job relevance* is "*the degree to which the technology was applicable"* (Marangunić & Granić, 2015, p. 186).
- *Output quality* is the extent to which the technology performs above quality standards.
- *Result demonstrability* is defined as the tangibility of the results.
- *Experience* is the accumulation of past interactions with the technology and the related evaluations of performance over time.

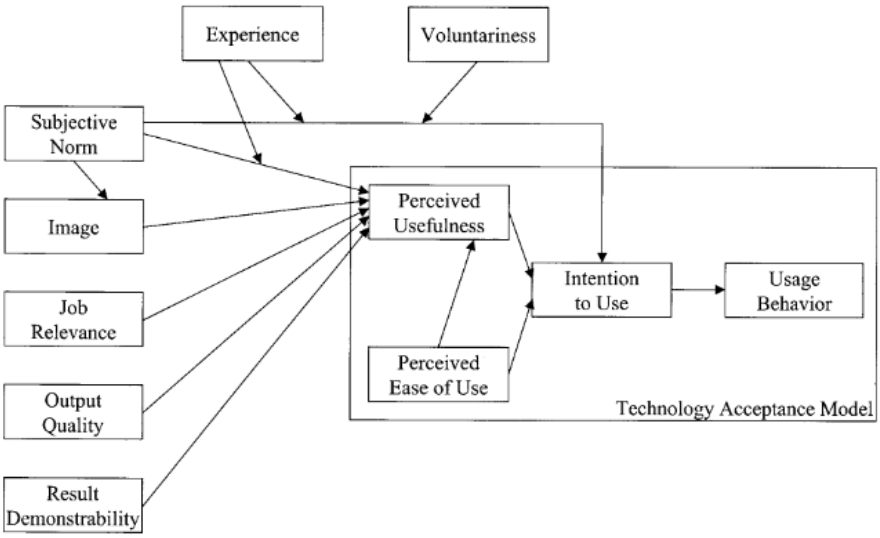


*Figure 4: The extension of the Technology Acceptance Model proposed by Venkatesh & Davis (2000) introduces two new processes, namely social influence (i.e. subjective norm, image and voluntariness) and cognitive instrumental processes (i.e. job relevance, output quality, result demonstrability and experience).*

Particularly relevant for this study are voluntariness and image. However, this model considers only determinants of perceived usefulness without considering perceived ease of use. Venkatesh & Davis (2000) justified their choice by claiming that as one's experience increases, perceived ease of use becomes nonsignificant. However, Venkatesh, in one of his later study showed that there are different determinants of perceived ease of use, for example, self-efficacy and computer anxiety (Venkatesh, 2000). In turn, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT).

### *3.1.6 Unified Theory of Acceptance and Use of Technology (UTAUT)*

The UTAUT claims the integration of different adoption models including most of the theories considered so far (Venkatesh et al., 2003). Verkantesh et al. (2003) included all the determinants that were significant in either predicting behavioural intentions, use behavior or moderating the relationship between these last two constructs. As shown in figure 5, the new determinants are (Venkatesh et al., 2003):

- *Performance expectancy* is the extent to which the customer believes that the technology is helping in achieving specific performance goals.
- *Effort expectancy* is the extent of effort needed to use the technology.
- *Social influence* partially relates to subjective norm as the extent to which a person is socially pressured to use the new technology.
- *Facilitating conditions* as the extent "*to which an individual believes that an organizational and technical infrastructure exists to support use of the system*" (p. 453).

The UTAUT also proposes four moderators between determinants, *behavioral intentions* and *use behavior*:

- *Personal characteristics* of the customer as *gender* and *age.*
- *TAM2 moderators,* namely *experience* and *voluntariness*.

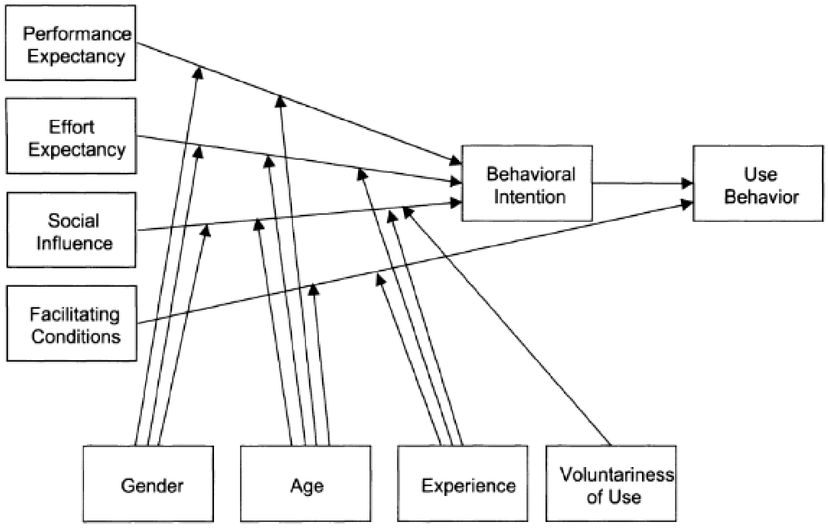


*Figure 5: The Unified Theory of Acceptance and Use of Technology proposed by Venkatesh et al. (2003) include several determinants from other theories to consolidate within one framework all the significant factors of technology adoption.*

Performance expectancy and effort expectancy are particularly interesting for the scope of this study. However, since the model is relatively new, it has considerable drawbacks in terms of validity and replication (Straub, 2009).

### *3.1.7 Trust-based models*

Several authors proposed as a theoretical basis to technology acceptance trust-based models, meaning that "*trust*" has a pivotal role in customer's decision. This construct does not have a standard definition when it comes to technology acceptance. Nevertheless, I adopt the definition of Hengstler et al. (2016), in which they define trust as "*the expectation that the trustee performs a particular action that is important to the trustor, irrespective of the ability of the trustor to monitor or control the trustee*" (p. 106). Trust is critical to reducing the perceived risk of a person and the consequences that derive from it (Liu et al., 2019; Luo et al., 2010). Initial trust in the technology is particularly influential for radical innovations (Hengstler et al., 2016) and industries as healthcare and transportation which directly risk people's lives (Fan et al., 2020). Therefore, this construct is a direct determinant of innovation resistance which if too high leads to technology failure. Trust depends upon different factors such as observability (Rogers, 2010), trialability (Rogers, 2010; Luo et al., 2010), technology understanding and faith (Hengstler et al. 2016). However, trust can be expressed in the technology itself but also in the innovating company and the message communicated (Hengstler et al., 2016). As a result, trust is a key determinant of a customer's intention to adopt, but the relationship may take various forms.

In the academic literature, there are several examples of trust-based models applied to AI technologies adoption. Hengstler et al. (2016) based their theory on the single determinant of trust to explain the acceptance of autonomous vehicles and medical assistance devices. Particularly interesting is Luo et al. (2019) that examine trust as a multidimensional phenomenon and how that applies to mobile banking services (Figure 6). The authors consider the different maturity stages of trust over the time distinguishing (Luo et al., 2019):

- *Disposition of trust* determines the initial trust of a customer towards the behavioral intention and it is defined as her inclination in adopting a trusting attitude.
- *Structural assurance* is the perception of trust determined by the institutional environment.
- *Trust belief* is the pre-existing trust which is determined by knowledge on the technology, company or other stakeholders around it.

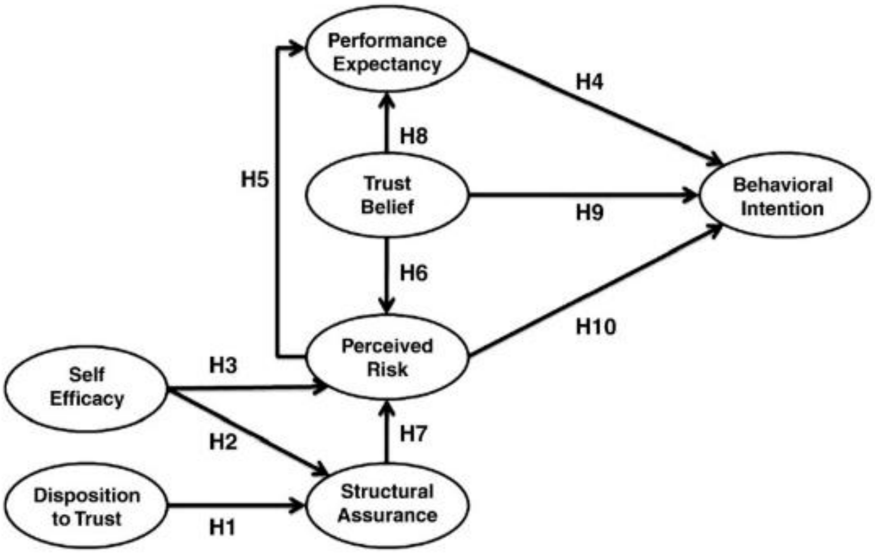


*Figure 6: The trust-based model proposed by Luo et al. (2019) examines the multi-dimensionality of trust (i.e., disposition to trust, structural assurance and trust beliefs) and how they relate to initial adoption.*

On the opposite, Fernandes & Oliveira (2021) consider trust as important but not as key determinant for the acceptance of automated technologies in service encounters. Their model integrates trust as a relational element together with social and functional elements as shown in figure 7 (Fernandes & Oliveira, 2021):

Functional elements:

- *Perceived Ease of Use* and *Perceived Usefulness* from the TAM.
- *Subjective Norms* from the TPB.

Relational elements:

- *Trust* defined as Hengstler et al. (2016).
- *Rapport* is a personal connection between the technology and the human.

Social elements:

- *Perceived Humanness* is defined as "*the anthropomorphic qualities that the consumer finds in a robot"* (p. 184).
- *Perceived Social Interactivity* is associated to the emotional and appropriate actions exhibited by the technology and compliant to society's rules.
- *Perceived Social Presence* defined as the extent to which an individual considers the technology as social entity.

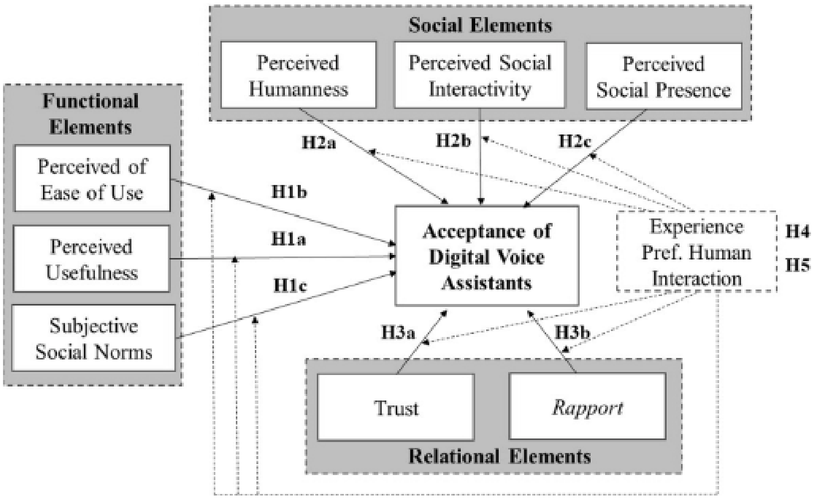


*Figure 7: The trust-based model proposed by Fernandes & Oliveira (2021) considers trust as relational element that together with social and functional elements determine the acceptance of Digital Voice Assistants.*

The common line between these examples is the type of technology which also AI is part of (i.e., automated technologies). However, all these models differ significantly from one another.

### *3.1.8 Summary and theoretical lens*

In the previous sections, I analysed seven potential candidates as suitable theoretical frameworks for this study. Four theories out of seven offer a robust theoretical basis, include social aspects within the technology adoption and relate to customer awareness and access to technical skills as leverage point for stimulating customer's acceptance. Starting from the first theory, DOI presents relevant social aspects as relative advantage, compatibility and complexity. In addition, the framework already presents applications in intelligent products (Talebian & Mishra, 2018; Balta-Ozkan et al., 2013). However, the model does not define how to stimulate adoption but rather why that happens (Straub, 2009). Next to this, although the development of AI-solutions registered a considerable increase, its acceptance does not follow the same pattern, being relatively at its early stages (Sohn & Kwon, 2020). Therefore, for the case of AI technology is better considering adoption individually.

Both SCT and TAM examine adoption at the individual level, but they take two different perspectives on the subject. SCT measures the customers' perceptions of the technology as *outcome expectations* while the TAM as *perceived ease to use* and *perceived usefulness* (Compeau, Higgins, & Huff, 1999; Bandura, 2001). Moreover, SCT consider the relations among its determinants as bi-directional capturing the dynamics between them. Self-efficacy has a pivotal role in predicting customer's final behavior. Nonetheless, the focus of this framework is on emphasizing the interactions between human and social environment and not on the technology itself. On the other hand, TAM is technology centred and focuses on the interaction between human and technology (Straub, 2009; Taherdoost, 2018). TAM is one of the most used frameworks available today to understand technology adoption. This is because TAM offers quantifiable constructs that describe a customer's propensity to adopt (Straub, 2009). In addition, its predictors build up on the social factors of SCT and DOI, namely self-efficacy, outcome expectations (performance), complexity and relative advantage

(Davis, 1989). However, the multiple extensions and its limited focus make the TAM lacking cohesion and adherence to reality (Straub, 2009). For these reasons, this model received multiple critics (Benbasat & Barki, 2007; Venkatesh, Davis, & Morris, 2007). Nevertheless, numerous authors still consider TAM as one of the most reliable frameworks for adoption forecasting (Sepasgozar et al., 2019; Venkatesh, Davis, & Morris, 2007). Therefore, the model resulting as the most appropriate one between DOI, SCT and TAM is the Technology Acceptance Model proposed by Davis (1989).

TPB is a fair alternative to the TAM since both derived from the same theory. However, TPB considers exogenous variables (e.g., social norms) while TAM focuses mainly on the relationship between the customer and the technology (Sohn & Kwon, 2020). TPB was initially developed with a broader scope of understanding human behavior while TAM was developed on purpose to understand technology adoption (Rahman et al., 2017). Again, as with the SCT and DOI, this weakness of the TAM is a point of strength for this study. One of the challenges of using TPB is in predicting technology adoption of specific target behaviors (i.e. social barriers; Venkatesh et al., 2007). Next to this, another major limitation of the TPB is that it assumes humans being rational taking decisions based on the available information without considering when this is not the case (Marangunić & Granić, 2015). In this research, TAM2, UTAUT and trust-based models were also considered next to the TPB and TAM. However, these three theories presented major limitations in reliability, validity and consistency.

Table 2 offers a summary of the constructs included in the seven theories and the considerations made in relation to the research question (i.e., advantages and limitations compared to the research question).

| Theoretical framework | Constructs | Advantages compared to the research question | Limitations compared to the research question |
| --- | --- | --- | --- |
| *Diffusion of Innovation Theory (DOI)*<br><br>*Proposed by Rogers (2010).* | • Time<br>• Social system<br>• Communication channels<br>• Innovativeness<br>a) relative advantage<br>b) compatibility<br>c) complexity<br>d) trialability<br>e) observability | • Consider several social factors within the technology aspect (i.e. relative advantage, compatibility, complexity and observability)<br>• Endogenous variables: Relative advantage, compatibility, complexity<br>• Applications on intelligent products available | • Consider the diffusion at a social system<br>• Explain why the adoption happens and not how to stimulate it |
| *Social Cognitive Theory (SCT)*<br><br>*Proposed by Compeau et al. (1999).* | • Computer self-efficacy<br>• Outcome expectations (performance)<br>• Outcome expectations (personal)<br>• Affect<br>• Anxiety<br>• Usage | • Consider the adoption individually<br>• Emphasis on social factors<br>• Bi-directional influences between determinants<br>• Pivotal role of self-efficacy<br>• One of the most used frameworks in technology acceptance literature | • Consider mostly social exogenous variables<br>• Focus is not on the technology itself |
| *Technology Acceptance Model (TAM)*<br><br>*Proposed by Davis (1989).* | • Perceived usefulness<br>• Perceived ease of use<br>• Intentions to use<br>• Actual system usage | • Consider the adoption individually<br>• Focus on the relationship between customer-technology<br>• Possibility to adapt the theory to specific circumstances<br>• Perceived ease of use and perceived usefulness includes key-factors of SCT and DOI (i.e. self-efficacy & complexity; outcome expectations – performance & relative advantage)<br>• One of the most used and reliable frameworks in technology acceptance literature<br>• Applications on intelligent products available | • Unidirectional influences among constructs<br>• Several extensions of the model cause lack of consistency<br>• Limited focus causes a lack of adherence to the reality |
| *Theory of Planned Behavior (TPB)*<br><br>*Proposed by Ajzen (1991).* | • Attitude towards the behavior<br>• Subjective norm<br>• Perceived behavioral control<br>• Intention<br>• Behavior | • Consider the adoption individually<br>• Endogenous variable: perceived behavioral control<br>• One of the most used frameworks in technology acceptance literature | • Focus is not on the technology itself (very broad scope)<br>• Assumption that humans do not take decisions unconsciously |

| Theoretical framework | Constructs | Advantages compared to the research question | Limitations compared to the research question |
|---|---|---|---|
| *Extended Technology Acceptance Model (TAM2)*<br><br>*Proposed by Venkatesh et al. (2000).* | TAM<br>• Perceived usefulness<br>• Perceived ease of use<br>• Intentions to use<br>• Actual system usage<br>Social Influence Processes<br>• Subjective norm<br>• Image<br>• Voluntariness<br>Cognitive Instrumental Processes<br>• Job relevance<br>• Output quality<br>• Result demonstrability<br>• Experience | • Consider the adoption individually<br>• Integration of social influence processes as image and voluntariness | • Focus on perceived usefulness ignoring determinants of perceived ease of use<br>• Social influence processes and cognitive instrumental processes consider mostly exogeneous variables |
| *Unified Theory of Acceptance and Use of Technology (UTAUT)*<br><br>*Proposed by Venkatesh et al. (2003)* | • Performance expectancy<br>• Effort expectancy<br>• Social influence<br>• Facilitating conditions<br>• Gender<br>• Age<br>• Experience<br>• Voluntariness of use<br>• Behavioral intention<br>• Use behavior | • Consider the adoption individually<br>• Integration of endogenous social factors as performance expectancy, effort expectancy, voluntariness, gender and age | • Limitations in terms of validity and replication |
| *Trust-based models* | • Depending on the authors but usually trust has a pivotal role in the model | • Consider the adoption individually<br>• Integration of trust as determinant<br>• Application mostly on automated technologies | • Not consistent |

*Table 2: A summary of the constructs, strengths, and weaknesses of the seven theories considered for this study.*

In this specific investigation, the focus on the individual's perceptions of the technology is what makes the TAM unique to answer the research question. First, the degree of AI acceptance among customers is not uniform, therefore it is critical to understand where the majority stands and what makes the difference between them and those who accepted it (Brock & Wangenheim, 2019). Second, exploring the relationship between customer and technology is of primary importance compared to external stimuli. Third, TAM includes important social constructs from other theories as self-efficacy, outcome expectations (performance), complexity and relative advantage (Grover et al., 2019; Venkatesh, 2000; Davis, 1989). Fourth, although the consistency of the TAM is the object of criticism, the flexibility of the model allows the researcher to analyse the beliefs of a customer regarding a distinct type of technology or innovation (Straub, 2009). Furthermore, additional studies recognized TAM as a reliable model, specifying use measures and application type as potential influences on the TAM's prediction ability (Turner et al., 2010; King & He, 2006). Each model analysed has its limitations as shown in Table 2. Nevertheless, TAM presents more significant advantages compared to the other theories. Therefore, despite the limitations of the TAM, I believe this model is the most appropriate framework for answering the research question. In the next section, I will apply the model specifically to AI technologies by exploring which social barriers influence perceived usefulness, perceived ease of use and intentions to use the technology. To identify these barriers, I will also consider some factors identified in this section from other theories and apply them under AI circumstances (e.g., trust).

## 3.2 Social barriers to AI adoption

In this study, I explored how individually customer perceives the technology and the social obstacles that come with it. These constraints are critical for the adoption of technology because they create resistance and keep the customer from accepting the product (Talebian, & Mishra, 2018). The social barriers do not consider the economic aspect such as the price or the technical complexity but rather its social aspect like safety or trust (Cubric, 2020). Therefore, in the context of this study, I define social barriers as social obstacles perceived by customers that hinder technology adoption.

The two major social challenges that customers face once interacting with AI technology are *access to technical skills* and *customer awareness* (Canhoto & Clear, 2020; Stix, 2018). However, academic literature recognizes other social barriers that prevent customers from adopting AI technology. The most common ones are *trust*, *safety*, *security*, and *job displacement* (Dwivedi et al., 2021; Arun et al., 2020).

### *3.2.1 Access to technical skills*

For a successful adoption, customers must train their employees on how to work with the new technology or access to skilled human capital. The absence of technological expertise increases the perceived difficulty of using the technology, which in turn, decreases the intentions to use (Fan et al., 2020; Balta-Ozkan et al., 2013). For example, the adoption of autonomous mining systems requires advanced training in "*data management, database structure knowledge, data mining, control systems, professional automation programming skills*" (Ali & Rehman, 2020, p. 11). These abilities go beyond basic computer knowledge and require access to expertise. Several authors recognised the necessity of advanced-data science skills (Raisch & Krakowski, 2021) or technical knowledge on AI-specific techniques as machine learning (Cubric, 2020; Canhoto & Clear, 2020; Brock & Wangenheim, 2019). However, the skills' specificity depends on the industry of application and on the solution itself. In their study, Brock & Wangenheim (2019) provide some guidelines for an effective implementation of AI within the context of digital transformation. The authors identify fours areas in which companies should focus the development of digital skills (Brock & Wangenheim, 2019):

1. *Strategic capabilities* defined as a comprehensive digital strategy of how to maintain competitive advantage and access to digital skills.
2. *Technology capabilities* defined as access to digital skills in new technology trends or on the specific solution that the company wants to adopt (i.e., AI).
3. *Data capabilities* defined as data management expertise.
4. *Security capabilities* defined as cybersecurity expertise.

Therefore, companies when adopting new technologies should engage in a broad-based investment approach combining technical implementation with human capital investments (Barro & Davenport, 2019). Human capital investments include training of employees, staffing or access to professional services (Ahn & Kim, 2017). As a result, if customers have access to the necessary skills, they will perceive the operational usage of the technology as less difficult. Therefore, I propose in this study that *access to technical skills* positively influences *perceived ease of use.*

### *3.2.2 Customer awareness*

Technology awareness is defined as "*user's knowledge about the capabilities of a technology, its features, potential use, and cost and benefits, i.e., it relates to awareness-knowledge*" (Rogers, 1995, p. 372). Customers that lack adequate knowledge of AI are prone to a polarization of their technology assumptions (Barro & Davenport, 2019). A too positive image of the technology creates unrealistic expectations on its performances (Canhoto & Clear, 2020; Cubric, 2020). In this case, the effects on technology adoption are determined by how quickly customers recognize their excessive positivism. If customers realize it before the adoption, they will overlook its benefits because they do not match the expectations affecting their intentions to use. However, if customers do not recognize it promptly, they would be blind to the technology's shortcomings and they would perceive the adoption as more difficult. Conversely, a too negative perception of the technology leads customers to weight the disadvantages more than the benefits, negatively influencing their intentions to use (Visser et al., 2020; Brock & Wangenheim, 2019).

Therefore, customer awareness encourages realistic assessment of the technology and investments in risk management practices in the short and long term (Canhoto & Clear, 2020; Balta-Ozkan et al., 2013). Risk management practices are crucial because they allow customers to manage strengths and vulnerabilities of the new technology within their specific contexts (Saeidi et al., 2019; Halliday, Badenhorst, & Von Solms, 1996). Thus, *customer awareness* positively affects both *perceived ease of use* and *perceived usefulness*.

### *3.2.3 Lack of trust*

Trust is an important determinant of technology adoption. However, it is important to distinguish trust towards the technology and trust towards humans (Fan et al., 2020; Lee & Moray, 1992). First, trust towards the technology is feeble, it builds up lower but drops faster compared to humans (Dzindolet et al., 2003). Second, trust towards the technology can be divided into trust in automation and trust towards the innovating firm and its communication (Körber, Baseler & Bengler, 2018; Hengstler et al., 2016). The first one, trust in automation, relies on performance, process, and purpose (Lee & Moray, 1992). Performance is the machine's technical competence, while process refers to how the automation occurs and is closely related to understandability (Dzindolet et al., 2003; Lee & Moray, 1992). Purpose is defined as the intended use of the technology, or in other words, the solution needs to be contextualized (Hengstler et al. 2016; Lee & Moray, 1992). There are different determinants of trust within these three dimensions (Hengstler et al., 2016):

- *Process* relies on determinants of DOI as cognitive compatibility, trialability and usability.
- *Performance* is determined by operational safety and data security.
- *Purpose* is dictated by contextualization of the technology and distance between the society and the solution.

However, Hengstler et al. (2016) identify other determinants of trust towards innovating firm and its communication.

- *Trust in the innovating firm* is ensured only by introducing the technology gradually into the market, particularly in case of radical innovation. Next to this, stakeholder alignment and transparency are key to establish trust.
- *Communication* must be proactive since the early stage of diffusion with concrete and tangible information. The message must be written in a way that avoids using expressions that can elicit negative emotions. Furthermore, the technology's advantages must be tailored to target groups.

Therefore, this barrier heavily depends upon customer knowledge and involvement in the development process. On top of this, communication has a steering role towards ensuring trust (Körber et al., 2018). A possible solution to overcome this social barrier is stimulating access to knowledge and engaging in a communication strategy that respects the points listed above (Fan et al., 2020; Visser et al., 2020; Luo et al., 2019).

However, academic literature has not reached a common consensus on how exactly this construct affects technology adoption. First, customers scepticism prevents them from taking advantage of the technology's capabilities (Visser et al., 2020; Ye et al., 2019). Therefore, *trust* influences *perceived usefulness* (Sánchez-Prieto et al., 2020; Wu et al., 2011; Tung, Chang, & Chou, 2008). However, in a study on psychosocial factors influencing AI adoption, *trust* is proposed as the moderator between *perceived usefulness* and *intention to use* (Ye et al., 2019). Second, this construct significantly contributes to defining the dynamics between perceived risk and the outcome involved. For this reason, several investigations on technology adoption propose *trust* as a direct determinant of *intention to use* (Fan et al., 2020; Luo et al., 2019; Tung, Chang, &

Chou, 2008). However, the outcome is not limited to the willingness of the customer to engage in a specific behaviour, but also the final act itself. Therefore, *trust* affects both *intentions to use* and *actual usage system*, directly determining technology acceptance and adoption (Fernandes & Oliveira, 2021; Sánchez-Prieto et al., 2020; Hengstler et al., 2016; Wu et al., 2011). However, most of these contributions agreed upon *trust* being determinant of *perceived usefulness* and *intentions to use*. Thus, in this study I consider this construct negatively influencing *perceived usefulness* and *intentions to use*.

### *3.2.4 Safety*

Safety is defined as a realistic threat to customers' physical well-being (Złotowski, Yogeeswaran, & Bartneck, 2017). Several authors recognized safety as one of the main obstacles to the adoption of autonomous solutions, particularly in industries like healthcare and transportation (Baccarella et al., 2020). In these industries, ownership of the consequences is essential because people's lives are directly at risks. Conversely, one of the major limitations of AI is transparency (i.e., failure transparency, judicial transparency, responsibility) and alignment with human values (Arun et al., 2020). Despite these issues have been added to the public agenda, no solution has been found yet (Dwivedi et al., 2021).

Hengstler et al. (2016) attribute safety concerns to a customer's lack of trust. However, it is not a rational evaluation of the technology that establishes safety concerns, but there may be differences between intuitive customer understanding and scientifically proven hazards (Hengstler et al., 2016). Delegating power over a machine elicits negative emotions, which, combined with a lack of trust in the technology, significantly decreases acceptance and adoption of the solution (Cubric, 2020; Złotowski et al., 2017). Therefore, it is true that safety concerns threaten the adoption of the technology, but they are not sufficient to determine that outcome (Hengstler et al., 2016). Safety follows the same pattern as *trust* since the absence of the latter reinforce the perception of the threat. If the customer delegates control over a solution that she does not trust, the fear of using the technology decreases her intentions to use. In addition, a physical threat to customer wellbeing reduces considerably her perception of the technology's benefits. Thus, s*afety* combined with a lack of trust, negatively influences customers' *perceived usefulness* and *intentions to use*.

### *3.2.5 Security*

The security barrier is a threat to the violation of customers' data and privacy (Arun et al., 2020; Paris et al., 2017; Wilson & Hash, 2003). However, in some cases, security applies also to safety, especially when by developing security standards it is possible to ensure people's physical wellbeing (Hengstler et al., 2016). Security is particularly emphasized in the healthcare and transportation industries. However, also in other sectors identified in section 2.2.2, security is prioritized, particularly when related to financial transactions or sensible data (Dwivedi et al., 2021). Another common aspect with safety is that *security* also reflects a weakness of AI that keep customers from trusting the technology (Paris et al., 2017). In 2020, Gartner predicts that the more AI solutions available into the market, the higher the number of points hackers can use for their attacks (Arun et al., 2020). For example, AI can be used to learn communication habits of a person and creating attacks by simulating those patterns (Arun et al., 2020).

Gilbert et al. (2003) recognized *security*, together with trust and other factors, as a strong determinant of *intentions to use*, while other authors described it as a barrier to adoption in general (Cubric, 2020; Brock & Wangenheim, 2019; Balta-Ozkan et al., 2013). However, security concerns present the same behavior of safety. They both are not sufficient to undermine AI adoption, but if reinforced by the absence of trust, they negatively influence *intentions to use*. Next to this, when *security* becomes a priority as in healthcare or banking services, it directly influences the *perceived usefulness* of a solution.

### *3.2.6 Job displacement*

Job displacement is defined as the replacement of humans in the workplace due to automation (Dwivedi et al., 2021; Fleming, 2019; Jarrahi, 2018). Digital automation makes obsolete half of the current jobs and AI could potentially contribute to one third of the total work displacement (Dwivedi et al., 2021). Its adoption can be quite disruptive in all the organizational aspect of a company, including its culture and people (Duan et al., 2019). However, this is not a new phenomenon because it was identified for the first time in 1930 by the economist John Maynard Keynes (Dwivedi et al., 2021; Fleming, 2019; Jarrahi, 2018). Therefore, job displacement started before AI was introduced into the market, but the recent speculations surrounding the technology has led people into believing that it will soon outperform humans (Fleming, 2019; Jarrahi, 2018). This belief generates fear and anxiety towards the technology and foment resistance to its adoption (Fleming, 2019; Ali & Rehman, 2020; Jarrahi, 2018). It is in this scenario of uncertainty that *job displacement* constitutes a social barrier to AI adoption (Cubric, 2020; Ali & Rehman, 2020; Złotowski et al., 2017).

On one hand, AI would undoubtedly replace some workers. On the other hand, this technology improves human capacities by increasing the value of cognitive and intuitive abilities (Grover et al., 2020; Kaplan et al., 2019; Jarrahi, 2018). Fleming (2019) backed up the idea that AI will not simply replace people's work, but it will change them. In his study on "*why robots might not want to steal your job"*, the author explains how the new work environment might look like. There will be three categories of jobs: (i) highly skilled workers, (ii) semi-automated occupations and (iii) jobs that are not worth automating. In fact, access to AI technology might be a considerable investment that not all companies can afford (Fleming, 2019). Therefore, job displacement cannot be avoided, but it can be regulated in a way that creates future opportunities. However, as well as safety and security, job displacement reinforces when trust in the technology is not present. Thus, *job displacement* negatively influences *intentions to use*. On the other hand, the customer might wonder whether AI is truly appropriate for her business as a result of this ethical controversy. Therefore, *job displacement* negatively influences *perceived usefulness*.

### *3.2.7 Influence of social barriers on AI adoption*

In this section, I answer the first question: "*Which are the drivers and social barriers to technology adoption recognized in the literature? How do these apply to AI?"*. First, I identify the drivers to technology adoptions through the Technology Acceptance Model initially proposed by Davis (1989). However, to better adapt the model to the research question, I adopted the extension proposed by Marangunić & Granić (2015). Second, I identified in the literature six social barriers: access to technical skills, customer awareness, lack of trust, safety, security and job displacement (Figure 8).

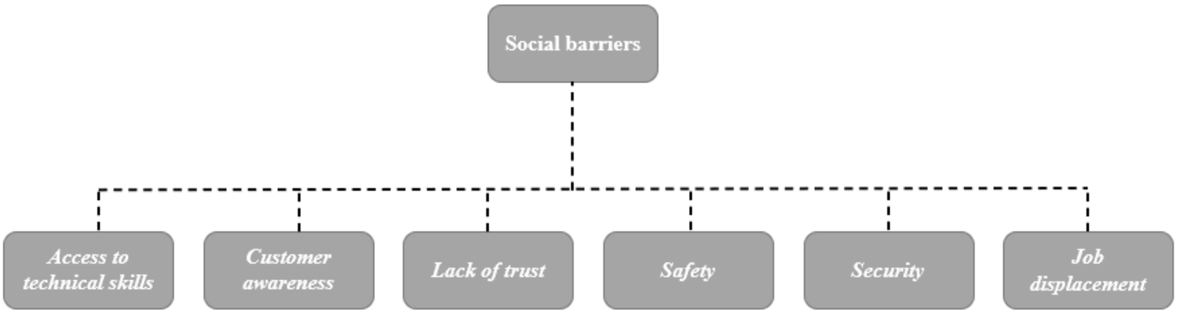


*Figure 8: The social barriers to technology adoption recognized more often from the academic literature are access to technical skills, customer awareness, trust, safety, security, and job displacement.*

However, *access to technical skills* and *customer awareness* differ from the other four social barriers. Firstly, they are direct determinants of *perceived ease to use* and *perceived usefulness* (Marangunić & Granić, 2015). Secondly, in general social constraints reinforce each other's effect creating technology resistance (Cubric, 2020; Złotowski et al., 2017; Hengstler et al., 2016). However, instead of reinforcing the effect of the other four barriers, *access to technical skills* and *customer awareness* balance their impact. Therefore, they are potential leverage points to overcome *trust*, *safety*, *security* and *job displacement* (Fan et al., 2020; Visser et al., 2020; Luo et al., 2019; Wilson & Hash, 2003).

Lack of trust is the barrier that is the most frequently cited and, in various models, it directly contributes to customer's decision to adopt (Fernandes & Oliveira, 2021; Luo et al., 2019; Ye et al., 2019). Safety, security, and job displacement are not only barriers to technology adoption, but also challenges that AI raises and for which there is not yet a solution (Arun et al., 2020; Duan et al., 2019; Fleming, 2019). Nonetheless, their single effect is not sufficient to determine a decision to adopt unless combined with trust. Thus, in this study, I propose the impact of *trust*, *safety*, *security* and *job displacement* as negative and reinforcing forces towards *perceived usefulness* and *intentions to use*. In figure 9 the complete model proposed in this investigation.

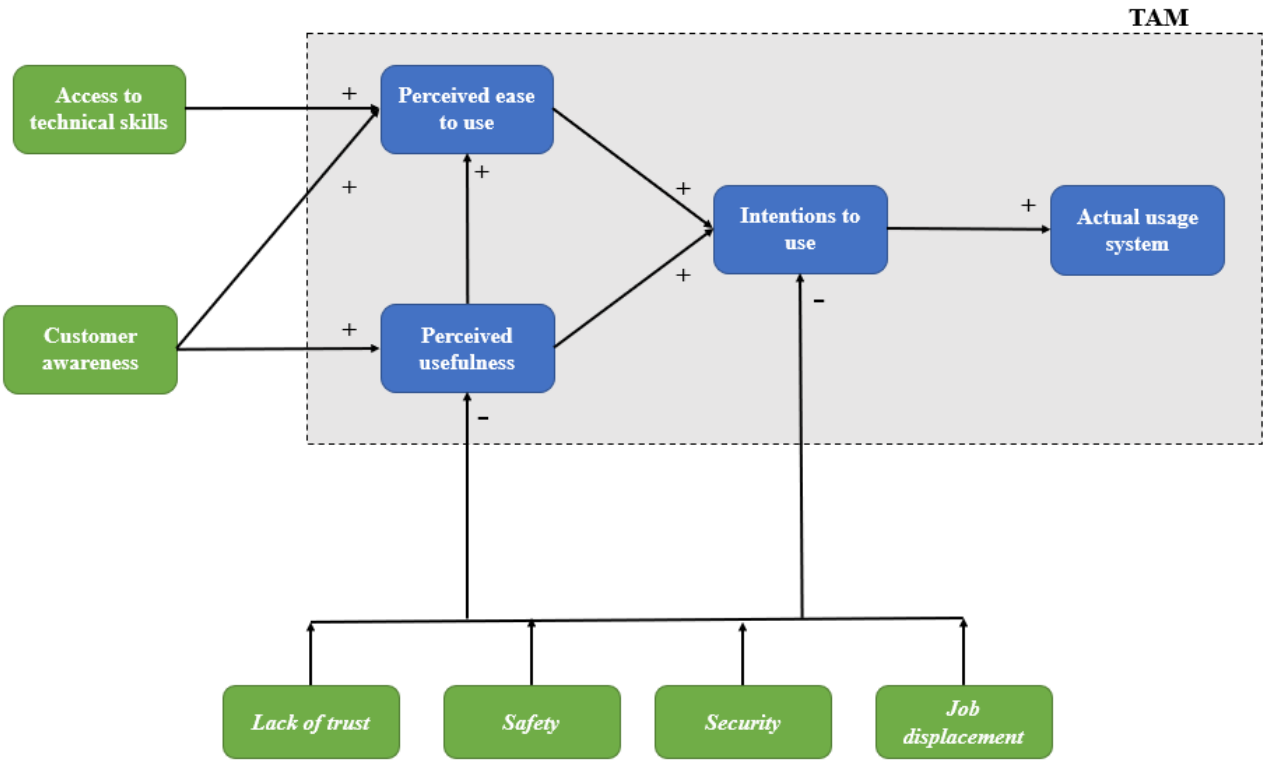


*Figure 9: The framework presented is proposed by Marangunić & Granić (2015) including the impact of the social barriers to the original TAM.*

Independently from the context of application, this framework captures the drivers and social barriers of AI adoption. However, as discussed in section 2.1 and 2.2, certain social barriers might be stronger across different countries or industry of application (Fan et al., 2020). In fact, if the technology can hinder people's lives or is directly related to the public interest, the social barriers trust, safety and security are particularly prioritized (Dwivedi et al., 2021: Hengstler et al., 2016). Therefore, in the next chapter, I investigate practices to create awareness and facilitate access to technical skills.

## 3.3 Best-practices to increase customer awareness and technical skills

Customer awareness and access to technical skills are both social barriers but also facilitating conditions (Grover et al., 2019). Technology awareness is not limited to the benefit of the technology, but it extends also to its limitations and applications (Paschen et al., 2020; Canhoto & Clear, 2020). Conversely, there are multiple possibilities to access to skilled human capital depending on the strategy that the company wants to adopt. Therefore, in the next sections, I explore how to create awareness and facilitate the access to technical skills.

### *3.3.1 Creation of customer awareness*

Awareness creation is the first step of a person's learning process, followed by training and education (Wilson & Hash, 2003). As a result, the primary goal of awareness creation practices is to generate fundamental information about the technology that can later be reinforced by training. There are different kinds of knowledge depending on its nature (Canonico et al., 2020; Lei, Gui & Le, 2021). Tacit knowledge is understood only by the individual and is difficult to identify and transfer because it expresses through the person's feelings, attitudes, and behaviour (Baldé, Ferreira, & Maynard, 2018). Conversely, explicit knowledge is more practical and can be communicated and interpreted by others (Berraies, Hamza & Chtioui, 2020; Baldé et al., 2018). The creation and transfer of information strongly depend on the interactions of these two kinds of knowledge, or also called "knowledge conversion" (Canonico et al., 2020).

However, to effectively create awareness, also the recipients of the information are important to identify. Awareness creation programs must prioritize specific target groups because people can have different understanding and interpretations of the subject. For example, to stimulate the introduction of AI into the industry, management education should be a primary concern (Barro & Davenport, 2019). Management defines the strategy of the company and the investment plans on intelligent technologies. Their polarization of expectations and opinions has far-reaching consequences than in a narrower domain (Barro & Davenport, 2019). On the one hand, underestimating the advantages of the technology reduces the company's competitive advantage (Saeidi et al., 2019). On the other hand, underestimating its limitations and consequent failure in implementing the technology create more resistance among employees (Barro & Davenport, 2019). Therefore, once management is aware of of the technology, the next goal is to transfer that knowledge to the employees who will interact with the new solution (Lei et al., 2021). Thus, to increase consumer awareness, it is essential to stimulate explicit knowledge, its connections with tacit knowledge, and to prioritize the company's management.

The SECI model is defined as one of the most influential frameworks used by researchers to explore the relation between knowledge creation and innovation (Baldé et al., 2018; Zelaya, & Senoo, 2013). It explains the process of awareness creation and how to stimulate the various interactions between explicit knowledge and tacit knowledge. The SECI model is a "*dynamic process, starting at the individual level and expanding as it moves through communities of interactions"* (Nonaka, Toyama, & Konno, 2000, p.12). In the SECI model there are four types of knowledge conversion (Figure 10; Nonaka et al., 2000):

- *Socialization* defined as "*the process of converting new tacit knowledge through shared experiences (...), such as spending time together or living in the same environment"* (p. 9). The transfer of tacit knowledge is stimulated by creating an environment that allows customers to share experiences through the participation of joint activities.
- *Externalization* is the second step of the SECI process and consists of converting tacit knowledge into explicit one via concept creation (i.e., model, prototype, or diagram). It is important to stimulate metaphors and analogy during the dialogue.
- *Combination* is the "*process of converting explicit knowledge into more complex and systematic sets of explicit knowledge"* (p. 9). Knowledge becomes more detailed and is integrated, synthesised, and disseminated through media (i.e., documents, meeting notes, or other material).
- *Internalisation* is the "*process of embodying explicit knowledge into tacit knowledge"* (p. 10). This step is closely associated with "learning by doing" and trialability. Personal experience, simulations and experimentations allow the customer to reflect upon the new information and internalise them into tacit knowledge.

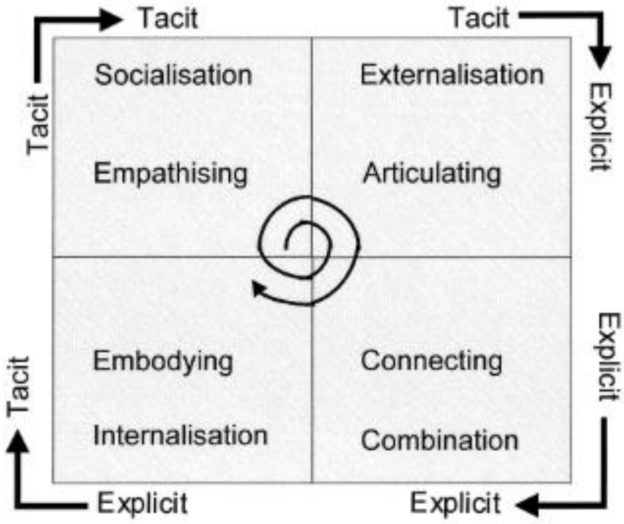


*Figure 10: The SECI process proposed by Nonaka et al. (2000) which includes four types of knowledge conversion: socialization (tacit-tacit), externalization (tacit-explicit), combination (explicit-explicit) and internalisation (explicit-tacit).*

The knowledge conversion is amplified at each interaction and up-grades continuously (Baldé et al., 2018; Nonaka et al., 2000). Next to this, Nonaka et al. (2000) also emphasized the importance of the living place in which knowledge is created and shared referring to the concept of *ba*. The *ba* goes beyond the physical space and it shares similarities with the concept of "communities in practice" (Canonico et al., 2020; Lievre & Tang, 2015). In both cases, members learn by being part of the community and actively participating in it. However, the *ba* changes quickly and does not have boundaries conditions for which participants can join or leave. Building a *ba* is important because it ensures quality throughout the SECI process (Nonake et al., 2000). However, although the *ba* creates the ideal conditions for promoting awareness, interactions are not possible without the activities defined by the SECI model. To build a *ba*, leaders must first dedicate a physical (or virtual) space that can stimulate such interactions (Canonico et al., 2020). Second, it is critical to select the people involved and understand the communities engaging with the technology (Tripathi et al., 2020). This part is also crucial to ensure the first step of the SECI model (i.e., socialization). Once the *ba* is set, leaders can design the awareness plan which consists of defining common goals, priority topics, the complexity of the information, methods, feedback collection and frequency of exposure (Wilson & Hash, 2003). These components are combined to form a communication strategy that fosters trust and interactions among participants (Wilson & Hash, 2003).

The uniqueness of this model is that it considers the process of knowledge creation as beyond organizational boundaries (Nonaka et al., 2000). In fact, the knowledge conversion involves actors within the organization but also externally (Bereznoy, Meissner, & Scuotto, 2021; Tripathi et al., 2020). For this reason, its application can vary from intraorganizational or interorganizational settings. For example, Baldé et al. (2018) propose it as a mean to drive creativity within teams of the same organization. Another example of intraorganizational application is offered by Allal-Chérif, & Makhlouf (2016) in which they analyse the impact of serious games on the knowledge creation processes of three financial firms (Allal-Chérif, & Makhlouf, 2016). Conversely, Tootell et al. (2020) applies the SECI model to explore the knowledge creation processes between university and industry context, while Lievre & Tang (2015) propose it between companies belonging to different cultural environments. In this study, the SECI model is used in an interorganizational environment in which potential customers and developers come together to foster AI awareness.

To conclude, the SECI model offers a valid representation of how knowledge is created taking into consideration its different essence. The knowledge creation process does not happen only within the company, but it goes across organizational boundaries and vice versa. Leaders should follow each step of the process and acknowledge that it is a never-ended process. In parallel, to ensure quality during the knowledge creation processes, leaders should follow the guidelines for the creation of a *ba* (Tripathi et al., 2020; Nonaka et al., 2000).

### *3.3.2 Facilitating access to technical skills*

The access to qualified people depends on the company's intentions to acquire new skills or outsource them. Thus, before analysing which is the best way to facilitate access to technical skills, it is important to understand the different sources of human capital and their limitations.

When it comes to procurement, management can choose between training the existing workforce and staffing (Barro & Davenport, 2019; Chen & Huang, 2009). Training is the second step in the learning process, and it differentiates from awareness because it focuses on the creation/reinforcement of skills useful to complete a specific task (Ahn & Kim, 2017; Wilson & Hash, 2003). Training programs are an investment in upgrading employees' skills, but the primary concern of management might be the monetary profit (Aguinis, & Kraiger, 2009). However, the return on training is measured not only in financial terms, but also in the generation of new ideas, involvement in company activities, increased employee motivation, and decreased resistance to change (Ahn & Kim, 2017; Sung & Choi, 2014; Chen & Huang, 2009). However, there are some disadvantages in financing this practice. The appropriability and effectiveness of the training is difficult to quantify (Aguinis, & Kraiger, 2009). Their effectiveness directly depends upon the readiness and motivation of the trainees (Baldwin & Ford, 1988). Besides, management must create opportunities for the trainees to practice their new skills and collect their feedback (Sung & Choi, 2014; Baldwin & Ford, 1988). Ultimately, effective training programs are not one-shot investments, but they must ensure continuity (Barro & Davenport, 2019; Chen & Huang, 2009). For these reasons, sometimes management prefers hiring new people than training employees.

Staffing is defined as the "*process of attracting, selecting, and retaining competent individuals to achieve organizational goals*" (Ployhart, 2006). This practice ensures diversity, access to advanced knowledge and skills, restructuring organizational culture and effectiveness (Ployhart, 2006). However, hiring new people poses two main challenges: (i) are educational institutes preparing new talents according to the industry's trends or should the company engage in training programs once new people are hired? (Ali & Rehman, 2020; Lewis, 2019; Despeisse & Minshall, 2017), (ii) how can the company retain/attract new talents? (Ployhart, 2006). In the case of AI, the first challenge appeared particularly prioritized. Ali & Rehman (2020) in their study on the adoption of the autonomous mining system, identified the education of new talents as essential for the success of the technology. Particularly, the authors emphasize the necessity of a strong collaboration between industries and educational institutes (Ali & Rehman, 2020). However, stimulating the dialogue between industry and governments is not always easy. Besides, staffing might be very time-spending especially when certain skills are not common in the market and difficult to retain. Therefore, companies often opt for professional services rather than staffing. This option allows the company flexibility and, at the same time, the advantages of hiring new people (Roodhooft, & Van den Abbeele, 2006). However, it creates a major expertise gap in the organization because know-how and skills are solely governed by consultants and externals (Roodhooft, & Van den Abbeele, 2006). Besides, access to these services is significantly expensive and not all companies can afford them in the long run. Therefore, outsourcing is not the alternative to the second challenge described above. Talents cannot be retained unless the company is willing to financially support such costs (Bruhn, Karlan, & Schoar, 2018).

Therefore, the sources identified have their own benefits and limitations. As a result, companies often engage in more than one option to ensure complementarities and to balance their risks. The best way to facilitate access to technical skills is ensuring the connections to all these sources in an effective way. The main advantage of being part of an ecosystem is the access to its network and benefit from its combined capabilities (Adner, 2006). From a biological point of view, ecosystem is defined as "*biological community of interacting organisms and their physical environment"* (Stam, 2014). From this definition literature evolved into "innovation ecosystem" and "entrepreneurial ecosystem". Both concepts are very close to each other and strictly related but they differ for their goals. The first one is defined as "*the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution"* (Adner, 2006, p. 2). Therefore, innovation ecosystem is innovation driven. The second one instead "*stresses how entrepreneurship is enabled by a comprehensive set of resources and actors, which have an important role to play in enabling entrepreneurial action"* (Stam, 2014, p. 2). Therefore, entrepreneurial ecosystem adopts a more holistic approach identifying entrepreneurship as the driving force. Entrepreneurial ecosystem puts at the centre the individual rather than the firm and it is based on specific components (Table 3; Stam, 2014):

- *Accessible markets* defined as the customer sphere.
- *Human capital or workforce* is access to skilled human capital and entrepreneurship.
- *Funding & finance* is the monetary investments and funding.
- *Support systems / mentors* defined as professional advisors or incubators/accelerators.
- *Government & regulatory framework* to facilitate entrepreneurship among the ecosystem members.
- *Education & training* is the access to training facilities and trainers.
- *Major universities as catalyst* to facilitate the culture of entrepreneurship and foster the link between industry and education institutes.
- *Cultural support* defined as the shared values of the members of the ecosystem.

| Pillar | Components |
|---|---|
| *Accessible markets* | Customers are small/medium/large companies.<br>• *Domestic markets*: customers from the same geographic area.<br>• *Foreign markets***:** customers from abroad. |
| *Human capital/workforce* | Talent management, entrepreneurial company experience, outsourcing availability, access to foreign talents. |
| *Funding & Finance* | Investments actors (e.g. angel investors, private equity, venture capital, etc). |
| *Support systems/mentors* | Mentors & advisors, professional services, incubators & accelerators, entrepreneurship network. |
| *Government & regulatory framework* | Innovation policies instruments (facilitations on starting a business, tax incentives, access to basic infrastructure). |
| *Education & Training* | Pre-university talents, graduated talents, entrepreneur-specific trainings. |
| *Major universities as catalyst* | Promoting entrepreneurship culture, stimulating the generation of new ideas and access to graduates. |
| *Cultural support* | Tolerance for risk and failure, preference for self-employment, success stories, research culture, positive image of entrepreneurship, celebration of innovation. |

*Table 3: There are eight main components of entrepreneurial ecosystem, namely accessible markets, human capital, funding & finance, support systems, governments & regulatory framework, education & training, major universities as catalysts and cultural support (Stam, 2014).*

As well as entrepreneurial ecosystem, also innovation ecosystem gives access to talents, knowledge and funding. Sometimes allocating resources to partners can be a better strategic decision than pursuing projects internally (Adner, 2006). However, it is also possible that actors compete for the same resources fostering opportunistic behaviours (Carnahan, Agarwal, & Campbell, 2010). This attitude is in contrast with the ecosystem's goal of jointly innovating towards a unique direction. Therefore, accessing to technical profiles within the ecosystem can raise tensions among partners. As a result, in both cases, being a part of an ecosystem provides access to qualified human resources and expertise regardless of the approach the business wishes to follow. Nonetheless, the holistic and individual-centred approach of the entrepreneurial ecosystem better facilitate access to trainers, new talents, connections with educational institutes and access to professional services without repercussion on the ecosystems' network.

## 3.4 Research significance

The rapid development of complex technology and autonomous solutions does not always coincide with customers' willingness to accept them into the market. The importance of this study is to understand how technology adoption can be stimulated by making the customer more aware of AI limitations but especially its benefits. The study specifically seeks to understand how an "inter partes" player within a well-established ecosystem can promote customer education and stimulate interactions between AI developers and potential customers in the Region. As such, the approach that AIIC adopted might need a revisitation after the outcome of this study.

Furthermore, although numerous authors identified several social barriers of technology adoption, few specifically addressed these issues. Most of the times, the economic and technical aspects of AI applications are prioritized over the social ones (Pan, 2016; Cubric, 2020). Conversely, literature well-recognises that customers lack the knowledge and skills to implement AI technology (Canhoto & Clear, 2020; Brock & Wangenheim, 2019; Balta-Ozkan et al., 2013). However, it is unclear where exactly the customers lack information (eg., benefits, limitations, technical applications) or skills (e.g., advanced data science, data management, etc.). Next to this, literature has not yet addressed how the TAM applies to AI in general but rather focused on specific application (Bawack et al., 2021). In fact, there are plenty of studies on its specific applications (Sánchez-Prieto et al., 2020; Wirtz et al., 2018), but none on its general acceptance and adoption. This because AI technology is highly context-specific, but it presents some common characteristics to its adoption that allow this study. Lastly, this master thesis focuses on a B2B market (Business to Business), while most of the studies on AI applications investigate the acceptance in B2C settings (Business to Consumers; Sánchez-Prieto et al., 2020; Sepasgozar et al., 2019).

# 4. Methods

This master thesis does not aim at testing theories but rather at theory-building from a case study. The problem-solving cycle is problem-driven, meaning it starts from the needs of a company (or multiple ones) to find a solution to a business problem (Van Aken et al., 2012). The definition of a business problem depends on the problem mess defined as a collection of circumstances that do not allow a clear vision of the problematic. As a result, the solution to this cycle is a context-specific theory based on a generalized one.

The identification of a specific business problem is the first step of the problem-solving cycle (Van Aken et al., 2012). In this report, it is referred to as the Preparation Phase, during which I recognized a specific problem statement, analysed the company's context, and the technology landscape. I retrieved this information from informal conversations with the company, secondary sources and preliminary screening of the literature. This step is critical to define the boundaries of the case study. In fact, to best address the research question and design a suitable approach for AIIC, this investigation adopts the case study approach. The case study emphasizes the "*contextual analysis*" (Cooper, Schindler & Sun, 2006, p. 150) of events and their interrelations, especially when the boundaries between the event and the context are not clearly defined. Case study research heavily relies on qualitative data and offers relevant insights for the problem-solving approach (Cooper et al., 2006). Another important consideration is that the selection of the case is not random and does not intend to represent the population. A theoretical sampling approach was used to select the case for this study because it is relevant "*for illuminating and extending relationships and logic among constructs*" (Eisenhardt & Graebner, 2007, p. 27).

Once the business problem and the boundaries of the case study are identified it is possible to move to the second step of the problem-solving cycle. This stage is called "Analysis & Diagnosis" (Van Aken et al., 2012) that aims at understanding the causes of the problem and validating them (Van Aken et al., 2012). For this reason, in this master thesis, the analysis part is divided into two phases. First, I conducted a literature review to build a theoretical foundation for my study. Second, I performed a qualitative analysis to investigate different aspects of my research questions. This last part aims at understanding where the customer lacks knowledge relating to AI, which skills are needed to stimulate adoption and validate the social barriers identified in the previous step. In parallel to the analysis, I coded the interviews while conducting new ones. By doing so, I adjusted my interview protocol in case some questions revealed to be unnecessary.

Once I summarized the results from the previous stage, the next step is the "solution design" (Van Aken et al., 2012). In this part of the process, I designed a solution that AIIC can adopt to achieve its goals. However, the actual implementation of the solution is not the scope of this master thesis. Therefore, the fourth and fifth stage, "Intervention" and "Evaluation", occurred together by organizing a focus group. The focus group allowed me to collect feedback about my solution in a time-effective way. The participants in the focus group were the all the members of the AIIC team. It is crucial to understand their considerations for the solution proposed since the AIIC members will implement the solution designed. Thus, through the focus group, I can validate my design and reflect on the research question. Once I implemented the feedback from the focus group, I presented the final solutions to the team and the company supervisor for a last validation. I concluded this investigation by drawing recommendations for future directions. The research process is summarized in figure 11 including data sources and the research deliverables provided at each stage.

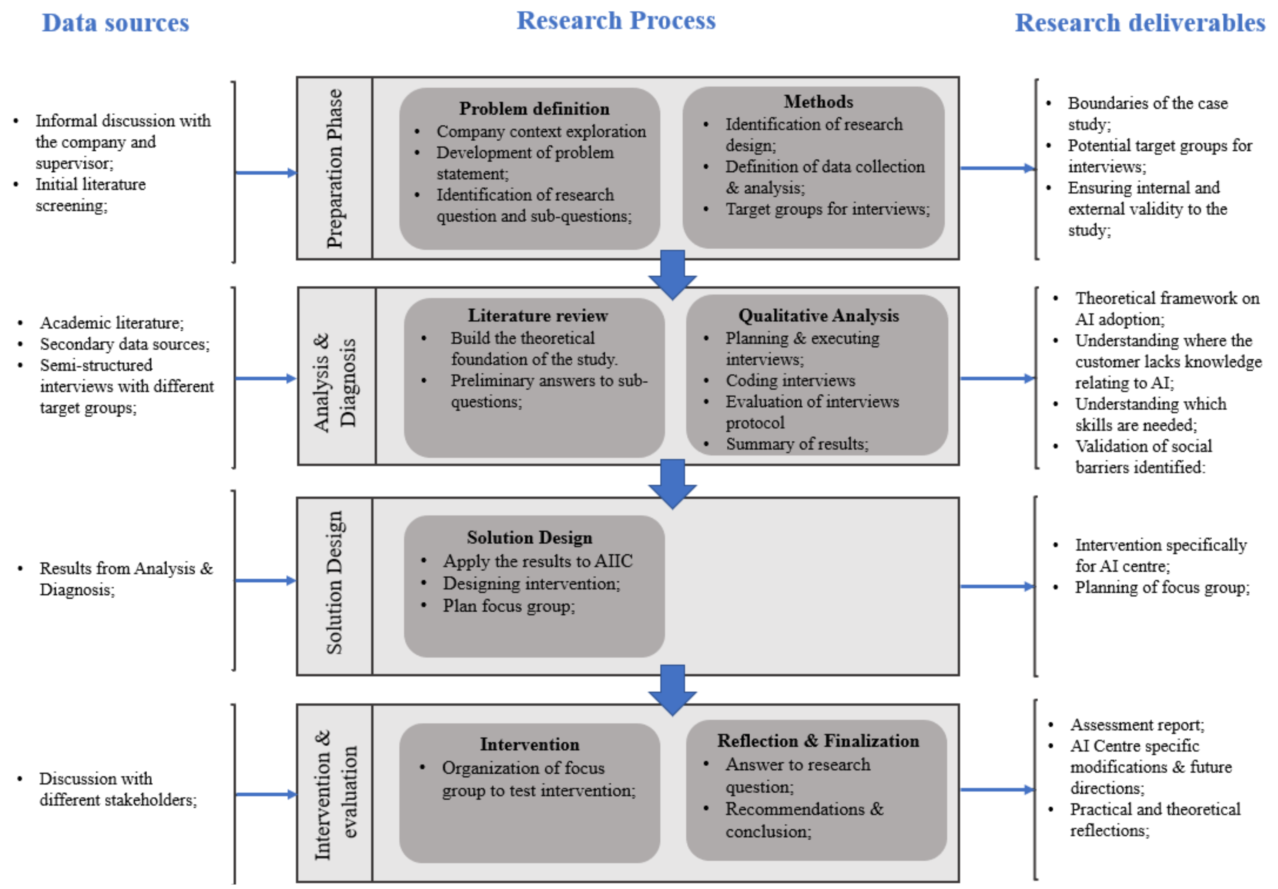


*Figure 11: The research process of this study follows the problem-solving cycle which is composed by five stages. In this picture, 'Intervention' & 'Evaluation' are represented in the same block since intervention does not entail to the actual implementation of the solution.*

## 4.1 Case study selection

AIIC is particularly relevant for this study for several reasons. First, AIIC is located within the High-Tech Campus, an ecosystem that fosters the development of high-tech technologies. This industry is identified as one of the driving forces to AI implementation (Paris et al., 2017). However, AIIC is also active in healthcare, smart environment, smart mobility, and new energies. Healthcare and smart mobility are both regarded as the two sectors with the highest social obstacles to AI adoption (Dwivedi et al., 2021; Baccarella et al., 2020; Fan et al., 2020). As a result, this study incorporates insights from both industries where the technology is already well-introduced and those where barriers to its adoption remain significant. This is extremely crucial considering that AI is a highly context-specific technology (Bawack et al., 2021; Paris et al., 2017). Furthermore, prospective customers are on the same campus and have already interacted with AIIC, taking the relationship to a degree of confidence. However, to increase the external validity of this report, I did not restrict interviews to only residents of the campus, but I also included companies from other European countries. Third, to overcome one of the major limitations of AI, namely transparency, developers must engage in a participatory development process (Hengstler et al., 2016). This is crucial because the "*participation of users and other stakeholders (…) is a powerful means to not only convince users of the technical features but also increase trust in the communication and the credibility of a firm"* (Hengstler et al., 2016, p. 114). Therefore, AIIC can embrace its 'inter partes' role and stimulate dialogues and information sharing from both sides. Customer awareness provides them with the necessary information to determine which solution is best. However, many businesses are hesitant to educate their customers since when visibility is generated by a single organization, the danger is a potential shift to competition (Bell et al., 2017). Besides, AIIC has the physical space and resources to build a *ba* (Nonaka et al., 2000) and encourage customer awareness in AI projects. Lastly, AIIC is an ecosystem that fosters the industrialization of AI technology in the Brainport region. Therefore, the members of the Centre benefit from access to talents, knowledge and funding (Stam & van de Ven, 2021; Stam, 2014; Adner, 2006). Furthermore, all the partners involved are part of HTC's larger ecosystem, which is the most active participant within AIIC. This allows AIIC to have access to resources that are not strictly related to AI, but they belong to a bigger scenario.

## 4.2 Data collection

The data collection phase consisted of two main steps that aim at reaching data triangulation. Data triangulation is the combination of different data collection methods on the same phenomenon (Jick, 1979). This approach ensures different characteristics depending on the type of triangulation. "Within-method" uses different techniques "*within a given method to collect and interpret data*" (Jick, 1979, p.602) and it assures internal consistency and reliability. "Between-method" uses two or more different methods to collect and interpret data and it ensures cross-validation. In this study, I adopted a "between-method" approach by combining academic qualitative data, observations during AIIC events and secondary sources.

First, I conducted a literature review to build a solid theoretical background on technology adoption theories, drivers and social barriers to AI adoption. This part is critical to define the boundaries of the research problem and distinguish the academic gap on the topic of analysis (Randolph, 2009). Second, I identified possible interviewees and using semi-structured interviews, I validated which social barriers are encountered by AI developers and customers, as well as customers' lack of knowledge and skills relevant to AI. Next to this, I integrated my findings with secondary sources to complement potential lack of information such as reports from the EU Commission, HTC internal investigation and AIIC documentation. A complete list is available in Appendix A. Furthermore, I frequently collected feedback from the company's supervisor and AIIC team. Lastly, AIIC organizes events bringing together different stakeholders to discuss relevant topics related to AI adoption. One example is the social aspect of technology adoption, particularly crucial for this master thesis. The recordings of the events are available as well as details on the time, and content (AI Innovation Center, 2021b). The multiple data collection methods and the related research questions are summarized in figure 12.

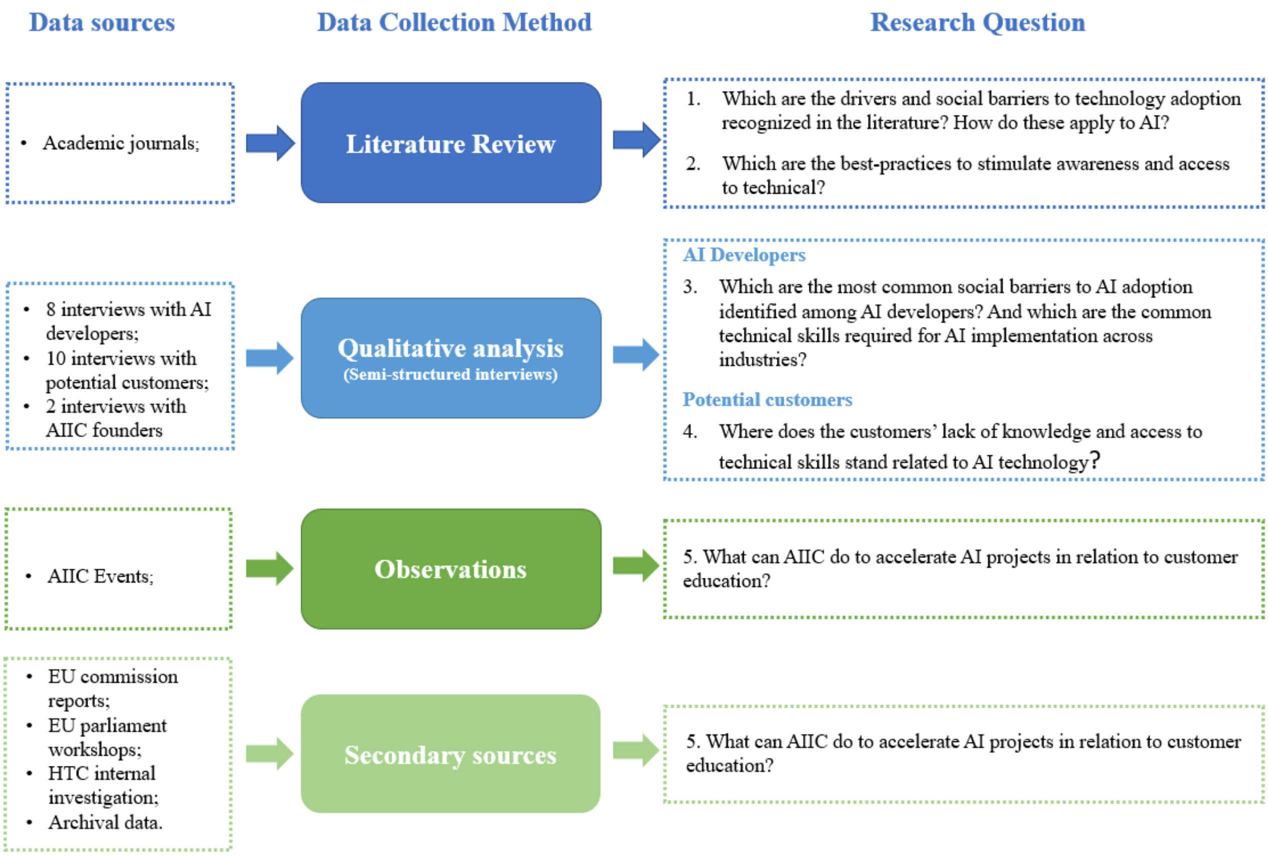


*Figure 12: The data collection of this study is composed by multiple methods including different sources of information among which literature review, qualitative analysis, observations and secondary sources.*

### 4.2.1 Literature review

The literature review produces a theoretical framework used to link previous findings with those of the current study (Randolph, 2009). The literature review started with the selection of appropriate academic articles based on the relevance to the topic and the journal of publication. If possible, also the number of citations received by the paper was a criterion of selection. However, to ensure that the topic was enough covered, I also applied the backward citations searching to the most relevant publications.

Therefore, I first identified the goals of the literature review which aims at defining drivers and social barriers to technology adoption and their contextualization regarding AI technology. Next to this, the literature review should identify which practices AIIC should engage to create awareness and access to technical skills. Secondly, I chose the database from which I retrieved the articles, namely Web of Science. This database allows quick identification of the significant contributions and most cited works (Singh et al., 2021). Next to this, the database is interdisciplinary, meaning that there are several disciplines available (Singh et al., 2021). This is crucial for the topic of this study because the academic literature has not reached a common opinion on the technology yet. However, some articles retrieved through backward citations searching were not available in Web of Science. Therefore, in this case I used also Google Scholar. The choice of Web of Science also offered direct access to the Journal Impact Factor (JIF). JIF is an important indicator that expresses the quality of the journal which is calculated through the yearly number of citations of the articles published in a given journal (Kurmis, 2003). There is not a distinct value from which a journal is considered as "good". However, due to the increasing attention in AI technology, it is crucial to distinguish significant contributions in the field. The rule of thumb considers JIF equal to 3 as the threshold for 'good' journals (Sci Journal, n.d.). Thus, in the collection of papers, I considered only publications with JIFs greater than 2.5, with some exceptions if the paper was classified as highly cited (i.e., above 100 citations).

I researched only academic articles published in English to facilitate understanding and I used specific keywords to identify the publications included in this master thesis: "*artificial intelligence*", "*technology adoption*", "*technology acceptance*", "*adoption theories*", "*barriers*", "*resistance*", "*awareness creation*", "*knowledge creation*", "*technical skills*", "*skilled human capital*", "*training*", "*staffing", "ecosystem", "entrepreneurship"*. Lastly, I combined these keywords with the operators "AND" and "OR" as following:

1. ["*artificial intelligence*" AND ("*technology adoption*" OR "*technology acceptance*" OR "*adoption theories*")]
2. ["*artificial intelligence*" AND ("*barriers*" OR "*resistance*")]
3. ["*awareness creation*" OR "*knowledge creation*"]
4. ["*technical skills*" OR "*skilled human capital*" OR "*training*" OR "*staffing"*]
5. ["*technical skills*" AND (*"ecosystem" OR "entrepreneurship"*)]

### *4.2.2 Semi-structured interview*

The semi-structured interviews are the first step to collect qualitative data and preparing it for later analysis. I decided to perform semi-structured interviews because they allow "*the exploration of the perceptions and opinions of respondents regarding complex and sometimes sensitive issues*" (Louise & While 1994, p.330). To understand the experience of AI developers and the customer knowledge, it is crucial to not steer the interviewee towards a direction that she would not have taken otherwise. Moreover, interviewees and interviewers might have a different interpretation of the same phenomena (Louise & While, 1994). For this reason, semi-structured interviews allow open questions and flexibility to dive deeper into specific directions.

At the beginning of this step, it is important to define the goals of the interviews to ensure the focus of the initial interview protocol on the research question(s) (Gioia, Corley, & Hamilton, 2013). I defined three kinds of interviews depending on the target group (Appendix B). First, I prioritized the interviews with AI developers to validate the social barriers identified in the literature. The reason behind this choice is that there is not a consensus on which are the social obstacles to AI adoption, and the experience of AI developers is critical to determine the most common ones. In the second part of the interview with this target group, I focused on identifying common technical skills that the customer should have access in order to adopt AI technology. Second, I interviewed potential customers to understand where their lack of knowledge stands (i.e., benefits, limitations, technical application). This allowed me to define the content of AI awareness. In total I interviewed eight AI development firms and ten potential companies that could use AI but have not done it yet. In both cases, I reached out to someone from the management of the company as the CEO (Chief Executive Officer), one of the founders or the program director. This to ensure that the company's future strategy and objectives were overall represented and up to date. Third, I interviewed the two founders of the AIIC to understand the requirements necessary to integrate the Customer Awareness Program (CAP) within their business model. For more details about the interviewees' characteristics see Appendix C in Table 6. Lastly, the interviews took place between May and June and they have been recorded, transcribed, and anonymized. If applicable, to increase accuracy, the transcripts have been reviewed and corrected by the interviewees.

To represent the perspective of each actor in the market, in both target groups I interviewed large companies (45% of the total interviewees), SMEs (33% of the total interviewees) and start-ups (22% of the total interviewees). In this study, start-ups are all those companies that started their activity very recently and have not reached the commercialization yet. These actors belonged to the three industry targets, namely smart manufacturing (50% of the total interviewees) and healthcare (50% of the interviewees). Lastly, to strengthen internal and external validity, I interviewed people from The Netherlands (67% of the total interviewees) and outside the country (33% of the total interviewees). An overview of the interviewees' characteristics is provided in Appendix C in Table 7.

### 4.3 Data analysis

This study is a case study research based on qualitative data analysis. The analysis of data is based on the inductive approach in which the researcher identifies patterns in the data without influencing the results with background assumptions (Charmaz, & Belgrave, 2007). According to this perspective, qualitative analysis is the direct result of a methodical approach in which data is collected, synthesized, and then analysed (Charmaz, & Belgrave, 2007). In the case of this investigation, data collection consists of conducting semi-structured interviews with the various subject groups. Data synthesis focuses on coding the interviews and identifying categories in which data are clustered based on certain commonalities. A single code is defined by Saldaña (2021) as *"(...) a word or short phrase that symbolically assigns a summative, salient, essence-capturing, and/or evocative attribute for a portion of language-based or visual data.*" (p. 3). The approach to coding can be deductive or inductive. The difference between the two methods is that the first one applies a fixed and pre-defined coding scheme driven by theory. However, defining an interview protocol based on current scientific theories might lead the researcher to lack insights into the interviewee's perspective and missing the discovery of new opportunities and concepts (Eisenhardt, & Graebner, 2007; Gioia, Corley, & Hamilton, 2013). In the case of this investigation, it is particularly critical to understand the perception that interviewees have without imposing any pre-existing assumption. For this reason, I adopted an inductive approach and open coding technique to analyse the data gathered.

Inductive research is often the target of criticisms due to a potential lack of rigour which interprets data as highly subjective and impossible to generalize (Gioia, Corley, & Hamilton, 2013). The inductive analysis of data is divided into two steps: (i) 1st order concept (synthesis) and (ii) 2nd order themes (data analysis). The first step consists of identifying codes and categories from the data. The second step is applying those categories to theory to describe the phenomena (Gioia, Corley, & Hamilton, 2013). In this regard, I use the software QDA Miner Lire to code several semi-structured interviews. To ensure "qualitative rigour" I followed the suggested procedure. During the 1st order concept, I created a codebook in which I defined each code used and its definition (see Appendix D, Table 8). Next to this, to strengthen consistency I referred to that particular code every time the transcript respected those conditions. As the interviews progress, I identified an overwhelming amount of codes that share some commonalities. Therefore, to reduce the codes previously identified I applied axial coding on the open code and classified each code into a category (Williams & Moser, 2019). I included these categories in the codebook to ensure qualitative rigour and consistency. Once identified the categories, the last stage of data analysis started (i.e., 2nd order themes). In this stage, I investigated links between the categories and the concepts or theories previously identified during the literature review. This final step in the process is to address the sub-questions and provide a tentative diagnosis of how the AIIC can approach its objectives.

# 5. Results

The interviews aimed at identifying the common social barriers to AI adoption as well as the technical capabilities required to successfully integrate AI across businesses. Next to this, the data obtained allowed the identification of customers' lack of knowledge in relation to technology features, benefits, limitations and potential uses. In the following sections, I present a detailed description of the findings of the interviews and the answers to the respective sub-questions:

3) *Which are the most common social barriers to AI adoption identified among AI developers? And which are the common technical skills required for AI implementation across industries?*
4) *Where does the customers' lack of knowledge and access to technical skills stand in relation to AI technology?*

## 5.1 Validation of social barriers to AI adoption

The results of the interviews from both target groups suggested the presence of the social barriers *access to technical skills, customer awareness, lack of trust, safety, security* and *job displacement* (see Appendix E in figures 19 and 20). All the AI developers interviewed were unanimous in recognizing *customer awareness, lack of trust* and *security* as obstacles to adoption. Next to this, the interviewees identified two additional barriers which are not novel to technology adoption theories, namely *internal support* and *social pressure* (see

Appendix E in figures 19 and 20). Moreover, on some occasions, AI developers had difficulty understanding the real motivations behind customers' refusal to adopt. This was caused by unclear information from the customers or inefficient communication towards them. This result highlights how sometimes AI developers do not recognise the existence of social barriers and consequently cannot act upon them (see Appendix E in figure 21).

### *5.1.1 Access to technical skills*

The analysis of the interviews of the first target group (i.e., AI developers) showed that *access to technical skills* is not one of the most common barriers to AI adoption. However, in these cases, AI developers provided ready-to-use products and did not recognize the necessity for the customer to access additional competencies. Nonetheless, the remaining respondents highlighted events in which the adoption became challenging due to out-of-date ICT human capital, absence of data management practices and tech-adverse employees. In some cases, AI developers themselves provided short training to end-users to reduce resistance to change and facilitate technological integration. One company selected its AI projects based on the technical maturity of the customers considered otherwise too resource intensive.

Conversely, potential customers expressed their desire to be taken by hand within an AI project and expected AI technology to adapt to their IT infrastructures. These findings demonstrate that access to technical skills is crucial to determine the extent to which technology is simple to implement and use:

> *"I think they need to know how the system actually works. Especially the older generations. I can imagine that if you have a car with a lot of buttons, they would like to know what they actually are and how they will benefit from it."* [Interviewee 6].

Next to this, the results highlight several qualifications to which customers should have access independently from the industry and AI-based solution. In section 5.2, I provide more information on these profiles.

### *5.1.2 Customer awareness*

The results of the interviews highlight how AI developers unanimously perceived that AI awareness is not present among customers. Users are not aware of the fundamentals of the technology and neither the state-of-the-art of their internal data. This is perceived as a significant obstacle when approaching AI projects:

> *"Customers that come to us with 'We have a lot of data, but we don't know what to do. Can you look at it?' We say sorry, you are not mature enough for us to come in like this, because this is a dead-end street. (...) There are so many data maturity steps that they need to overcome that are very hard."* [Interviewee 5].

This outcome is confirmed from the interviews with potential customers. The opening question of each interview was to define "Artificial Intelligence". Less than a half of the respondents recognised AI as a self-learning system that can improve over time. Table 9 in appendix F presents an analysis of the answers provided by the customers.

Despite the fact that most of the potential customers expressed support for the technology, they were unaware of the possible applications of AI within their industry, or within their organization. Customers that did not recognize any business case within their market, also considered the technology as immature. Numerous AI developers who were aware of this problem, created use cases to emphasize the importance of the benefits and how the technology should be used within the company. This was especially encountered in the healthcare sector, where professionals are concerned about the scientific validation of the solutions presented. Therefore, *customer awareness*, particularly through showcasing, positively influences customers' *perceived ease of use*.

Furthermore, most interviewees described AI in the perspective of its short-term benefits, such as improved data interpretation, increased efficiency, and performance. However, only a few of them identified its long-term advantages as well as its limitations. This finding suggests the presence of a polarization of customers' expectations towards the technology. Some customers were fully supportive of AI and did not recognise any obstacle:

> *"I do know what I want from the technology, but I don't even know if everything in my head is possible. I might make it so much possible than what it is."* [Interviewee 18].

On the opposite, other customers were against AI and were not able to recognise its benefits, which negatively influenced their intentions to use AI:

> *"I'm not directly in favour. Luckily in my company I share the conviction of my people that we do not really have an employment for AI yet."* [Interviewee 9].

In both cases, customers were unable to balance the benefits and drawbacks of new technologies. This is supported by the fact that AI developers observed a lack of readiness among customers to embrace AI's experimental nature. As a result, the findings of the interviews revealed that *customer awareness* positively influences both *perceived ease of use* and *perceived usefulness*.

### *5.1.3 Lack of trust*

AI developers unanimously declared that the market does not trust the technology yet. This finding was confirmed by most of the customers which expressed their mistrust while describing the technology's impact. Trust towards the technology builds up towards two main paths, namely trust towards automation (i.e., performance, process and purpose) and trust towards the innovating firm (Hengstler et al., 2016). The results of the interviews show that *purpose* is where mostly resides customers' lack of trust. The contextualization of the technology is missing from most of the potential customers since they are not fully aware of its potential applications, benefits and limitations. Dealing with uncertainty and delegating control over the system are the most common reasons for a lack of confidence by both target groups. Next to this, the distance between the society and the solution is still quite felt by the potential customers. AI developers declared that sometimes there is a certain discomfort among customers while talking about this technology:

> *"For this example that I give you, who cares how we do it whether is AI or different algorithm we use, but if you say is AI project you have certain measures and certain discomfort in it. A lot of discussions are overloading these projects."* [Interviewee 1].

This finding is also confirmed by customers interviews which identified ethical aspects as one of the reasons for companies to not trust AI:

> *"By AI some logic comes out. We do not understand the algorithm, we assume that it is statistically right, but as individual statistics do not apply to you. You might be the percentage that it is different."* [Interviewee 9].

However, these aspects influence also how the customer perceives that the automation is occurring (i.e., *process*) and the technical capabilities of the technology (i.e., *performance*). Therefore, trust towards AI is considerably lacking among potential customers. Conversely, AI developers recognized that customers establish trust in the innovating firm, but that communication plays an important steering role. The communication strategy must be carefully designed, particularly before the first interaction. AI developers acknowledged that the first impression was crucial to predict future desired outcomes:

> *"It also means that the first introduction is the most important. If in your first introduction you don't do what you promised, they will never trust you again. You have to be very clean and clear on how you communicated both expectations and constraints of the technology."* [Interviewee 4].

Most of the AI developers noticed that one efficient way of overcoming this barrier was to involve customers during the development of the solution. This is done by introducing intermediate checks where professionals interact with the technology and either confirm or deny the outcomes of the solution:

> *"How did we convince the doctors to work with the solution? We had the doctors helping us to fill the system and to train it by filtering out wrong information. (...) Convincing the doctors while helping them was not easy, but they realize it once using it that it was helpful."* [Interviewee 2].

This practice was often found to be successful within the healthcare sector. Therefore, lack of trust not only negatively influenced *intentions to use*, but also customers' *perceived usefulness* by preventing the customers from recognising the benefits of the technology.

### *5.1.4 Safety*

Safety was perceived as a barrier to AI adoption by both target groups. However, there is an important distinction to make regarding how it manifests itself in the healthcare sector and smart manufacturing industry. In the first case, safety was not identified as a physical threat to human wellbeing. Within the healthcare industry, this barrier manifested as a key limitation of AI, namely algorithm transparency. Potential customers were concerned about the lack of outcome transparency and the heterogeneity of data. Next to this, AI developers declared that healthcare professionals find it difficult to delegate the ownership of the decision and relying on AI:

> *"(...) they want to see a way that they remain in control. They are responsible for what happens to the patient and they want to keep that responsibility."* [Interviewee 16].

This finding exemplifies why the healthcare sector is one of the slowest industries in terms of AI adoption. However, as mentioned by some AI developers, if the customer trusts the technology, the burdens just mentioned are less felt:

> *"I think the biggest fear is that their patient is not represented in the dataset by which the algorithm has been trained. Therefore, they are confronted with an outlier in the data without knowing. (...), relying without knowing the outcome, but that's something you don't have if you receive trust."* [Interviewee 4].

This finding shows that trust and safety are strongly linked with each other and that in absence of trust, safety becomes an important social barrier. Such insight also applies to the smart manufacturing industry where safety is perceived as a physical threat to humans with consequent legal implications. Therefore, this investigation suggests that *safety,* together with *lack of trust,* negatively influence customers' *intentions to use.* However, the results of the interviews did not confirm a negative influence of *safety* on customers' *perceived usefulness.*

### *5.1.5 Security*

From both target groups, security is recognised as a potential threat to the violation of customers' privacy, the use of data for other purposes than the one claimed or being vulnerable to external cyberattacks. Cybersecurity and transparency are significant constraints of AI that have yet to be addressed. However, the results of the interviews show that security is not directly related to AI per se, but rather to new technologies and data collection practices existing in the market:

> *"I think AI needs the data to be trained on, so there's always a privacy concern. That concern is there also without AI. (…) I think is more about awareness. Being aware of what is going on is very important and I think a lot of people lack in this. AI relies on data, but the data collection happens anyway."* [Interviewee 10].

Moreover, customers are afraid that their data can be used by AI developers for different purposes than the ones stated at the beginning of the agreement. This manifests particularly when customers do not trust the innovating firm. Consequently, their *intentions to use* diminish considerably:

> *"We are a big tech-company and as others we work with data. (…) they are very much afraid that we are taking advantage of their data and produce something that we can leverage ourselves."* [Interviewee 2].

This is especially happening within the healthcare sector where customers are afraid of sharing patients' data and where data minimization[1] is still an issue. AI developers and customers might have different perspectives on the "minimal level" of personal data necessary to train the algorithm. Next to this, AI developers believed that Europe was not homogeneously addressing this issue. The interviewees referred that there are several regulations in place for each European country, preventing a united front on this topic. For example, several AI developers declared that Germany is one of the strictest European countries in terms of security. Some of them gave up on the idea of entering the German market in the incoming three years.

Therefore, this study confirms that when the customer does not trust the technology or the innovating firm, *security* becomes a priority, negatively influencing customers' *intentions to use.* Conversely, as with *safety,* the results of the interviews did not highlight any effect of *security* on *perceived usefulness*.

### *5.1.6 Job displacement*

Job displacement is perceived by most of the AI developers as a barrier to AI adoption. However, there is a dissonance between what is stated by AI developers and potential customers. AI developers recognised job displacement as a concern based on their experience while talking with management but also with the end-

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[1] Data minimization is defined by Pfitzmann & Hansen (2010) as the practice of minimizing the collection of personal data to the strict necessary as well as the storing time.

users. Conversely, the potential customers interviewed were mostly from management and the technology would not have affected their daily tasks directly. Potential customers recognised that AI did not initiate digital automation, but certainly, it increases its speed. Many of them declared that there will be a shift in job demand and that although some jobs will become obsolete, others will be created:

> *"I don't think that exists. History has shown that the more development we do, the more hardware and software we develop, it keeps more people from the streets than before. Of course, some jobs are lost but an amount of new jobs is added to it."* [Interviewee 9].

Moreover, potential customers perceived AI as a decision-support tool that augments humans' cognitive and intuitive capabilities. Therefore, AI is not seen as a competitor, but rather as a support tool. This means that *job displacement* is not an initial obstacle to adopt AI, but rather in its later acceptance within the company. AI developers declared that most of the time end users are concerned about the new skills required for the work, the changes in terms of performance, but especially, of losing their job. Therefore, end-users are aware of the impact that digital automation can have on their current employment and explains the initial resistance to adopt the technology. Conversely, although management did not recognise *job displacement* as an obstacle to AI adoption, it acknowledged the need of a governmental action in guiding the long-term transition:

> *"I believe that the government is responsible that the transition is guided. You cannot just find another job, you must re-educate people."* [Interviewee 11].

Next to this, AI developers declared that in the short-term, what makes the difference is how the technology is presented to the users. The importance of the value delivered must be prioritized over the technicalities of the solution creating trust among employers. Next to this, AI developers must first approach the management and then agree on how to introduce the new solution within the company. By doing so, end users' resistance to change decreases. Therefore, the negative influence of *job displacement* on the *intentions to use* depends on the presence of *lack of trust*. However, interviews results did not confirm any effect of this barrier on customers' *perceived usefulness*.

### *5.1.7 Internal support*

The results of the interviews highlight inefficient *internal support* as a common obstacle to AI adoption. This barrier was not considered at the beginning of this study, but it is not novel. The UTAUT identify it as a determinant of "Use Behavior". However, within this model, this factor is considered as "Facilitating Conditions" and defined as the extent "*to which an individual believes that an organizational and technical infrastructure exists to support use of the system*" (Venkatesh et al., 2003, p. 453). AI developers declared that sometimes there is a lack of internal infrastructures and processes which do not allow the adoption to proceed. Customers expect the technology to adapt to their internal situation and when this does not occur, their *intentions to use* diminished:

> *"There are so many pilots at this time, if we work on that is how can we include them in the infrastructure of the hospital. If we have a variety of solutions, the question is how do we make an integrated part of the hospital? That's something to work on it."* [Interviewee 16].

In other cases, the current infrastructures and processes were not the issue, but the human factor was steering the adoption. AI developers registered a lack of change management or, more in general, a lack of support from the management of the company. However, as mentioned by Venkatesh et al. (2003), the organizational and technical infrastructure are important elements to stimulate adoption. Therefore, *internal support* positively influences customers' *intentions to use*.

### *5.1.8 Social pressure*

At the beginning of this study, also social pressure has not been considered as a social barrier to AI adoption, but the findings from the interviews highlighted the opposite. Social pressure as well as internal support is not new to adoption theories. In the TPB and TAM2, this component is expressed through "subjective norms" (Ajzen, 1991; Venkatesh & Davis, 2000), which later relates to "social influence" in the UTAUT (Venkatesh et al., 2003). In all these cases, social pressure is attributed to the social urge to comply with the use (or not use) of this technology. AI developers highlighted four actors that determine this barrier, namely external and internal stakeholders, competitors, society and governments. However, not all of them had the same perspective in relation to AI adoption. On one hand, internal and external stakeholders were not always aligned:

> *"We had the workers counsellors saying, "we have not been working in this project we cannot accept that you use a tool like that, because it is able to oversee workers in their work." (...) Now the only people that were positive about our work were the workers themselves".* [Interviewee 1].

On the other hand, some AI developers recognised the presence of mimetic isomorphism within the market, meaning that organizations try to cope with uncertainty by imitating other firms (Dimaggio & Powell, 1983). Therefore, the actions of early innovators have a considerable impact on the market:

> *"Some countries or sectors adopt something, and the others follow because they know that they are good. If they see that everybody in their environment that adopted that technology is doing good, they will as well."* [Interviewee 3].

As regards society pressure, AI developers perceive that AI has not been accepted yet. The multiple ethical debates around it are overloading the projects with uncertainty. Next to this, AI developers feel pressure to comply with certain regulations imposed by governments that undermine the development of AI instead of stimulating it. Therefore, it was difficult to determine if the overall impact of *social pressure* on *intentions to use* was positive or negative. However, in this study *social pressure* positively influences *intentions to use* in relation to AI adoption in line with TPB, TAM2 and UTAUT.

## 5.2 Technical skills required for AI implementation across industries

One of the interviews' goals was to identify which skills companies need for AI implementation. Interviewees had difficulties in understanding and identifying specific skills. Some of the respondents asked to reformulate the question, others tried to answer but without mentioning particular competences. Some examples are reported below:

> *"The technical person usually is the one who has technical requirements. They need to know how to deal with this kind of software."* [Interviewee 3]
>
> *"In order to have self-driving technology to work, they need a lot of expertise especially on the technology. You need AI experts, which are very hard to find."* [Interviewee 6]

> *"I never thought about this. (...). People should understand which are the boundaries of AI, you cannot solve anything with just one system."* [Interviewee 15]

Nonetheless, some of the AI developers were able to distinguish job profiles that would help AI adoption by providing examples or directly mentioning them (see Appendix E in figure 22). Interviewees frequently identified the profile of the *data scientist* as initiator of this technology. However, the option of self-developing AI might be resource-intensive and not always the best strategic choice:

> *"However, at the end what you develop needs to be scalable, and secondly how do you assure that what you have developed has a proper support, a quality management system around it, that while benchmarking with international standards you can still use it."* [Interviewee 2]

Thus, customers frequently choose the second alternative, which consists of collaborating with organizations that are specialized in the development of this technology (i.e., *AI developer company*). In doing so, customers usually do not need access to further data-science skills.

However, AI is a context-specific technology where industry-oriented knowledge is essential for its successful development. The results from the interviews highlight how most of the times only experienced data scientists or AI developer companies also have industry knowledge. As a result, some AI developers involved *expert end-users* as much as possible during the validation and testing of the solution. Next to this, AI developers highlighted the need of different professions not related to the technology itself as *AI ethicists* and *lawyers* (see Appendix E in figure 22):

> *"I think they should always have experts before they put it into practice. Experts in privacy, security, the law and ethics. If dealing with human data, or if not with the GDPR, (...) is very important to have professionals around you to advise how to do it."* [Interviewee 5]

However, on some occasions the access to these professions might be challenging. For example, results also show the importance of a *hybrid profile* involved into the implementation of the technology, but at the same time, there is a lack for suitable candidates. In fact, respondents claimed that traditional professions are highly competent in their field of study, but with low (if not existent) experience on future technological or industry trends:

> *"I don't think that there are any educational curricula that form you for this. It should be somebody between ICT and medicine that knows what kind of data has been produced. I think you can write a profile that has technical side and business side. (...). It's easier to write the profile than hiring them."* [Interviewee 2].

Several interviewees recognised the need of integrating within the traditional study programs, courses or activities that would allow future candidates to be familiar with either an industry or a particular technology. Therefore, depending on the competencies required, some profiles might be easier to access compared to others.

Independently from the customers' approach to the development of the technology, the quality of data and their infrastructure is critical for a successful AI adoption. AI developers declared that multiple times customers have no idea of their internal data or they are not aware that the infrastructure they are currently using is too obsolete to proceed with an AI project. Consequently, the development often incurs in false starts which delay the release of the product and do not allow developers to deliver upon the expectations. In this regard, AI developers mentioned *data steward, data custodian, data architect* or *data quality manager* as profiles that could help customers with this gap, and consequently, facilitate AI adoption (see Appendix E in figure 22):

> *"The biggest gap that I have found so far in practice is less about the understanding of AI as such, but more about a general view of how to manage IT departments. (...) the most frequent reason why customers decide to not proceed is that they do not have the suitable infrastructure out in place."* [Interviewee 3]

Next to this, AI developers highlighted how the business translation stage can be challenging if customers cannot set the boundaries for the problem definition. In this regard, results show that AI adoption could be facilitated if customers had access to certain qualifications as *business translators* or *analytic translators* (see Appendix E in figure 22):

> *"We use the CRISP-DM methodology to do our projects which always starts with business understanding. (...) If the customer has someone that can facilitate the business understanding process to analytical process, then the starting point would be easier because they understand the risks."* [Interviewee 5]

Therefore, AI developers identified in total 12 profiles that are key to facilitate AI adoption: *data scientist* or *AI developer company, AI ethicists, lawyers, expert end-users, hybrid profile, data steward, data custodian, data architect, data quality manager, business translators* or *analytic translators.*

# 6. Discussion and preliminary solutions design

The goal of this chapter is to design preliminary solutions that AIIC can integrate within its business model to both support customers in accessing technical qualifications and providing them with the fundamental knowledge necessary to adopt AI. The solutions designed in this section based their fundamentals on the theoretical analysis in chapter 3 and the findings of the interviews in chapter 5. As a result, in section 6.1, some considerations are addressed to bridge the theoretical foundation with the findings of the interviews.

## 6.1 Discussion

The discussion that follows first address the influence of the social barriers on AI adoption by revising the model presented in section 3.2.7 and considering the additional two obstacles, namely *internal support* and *social pressure*. Second, it describes the 12 qualifications identified by the interviewees as well as the fundamentals for one of the proposed solutions.

### *6.1.1 Revised impact of social barriers on AI adoption*

The findings of this investigation suggest the presence of eight social barriers to AI adoption. Going with order, the first obstacle considered was *access to technical skills*. Several authors identified the necessity to access to specific technology-oriented competences like data-science skills (Raisch & Krakowski, 2021; Ali & Rehman, 2020). This outcome turns out to be true. Independently from the customers' wishes of developing themselves the technology or approaching AI developers, the access to data science expertise is needed. However, access to technical skills can go also beyond AI-specific competencies (Cubric, 2020; Canhoto & Clear, 2020; Brock & Wangenheim, 2019). Nonetheless, the specificity and type of skills strongly depend on the industry and the AI application itself. These outcomes confirm the necessity for customers to invest in human capital together, if not before, with the technology (Brock & Wangenheim, 2019; Ahn & Kim, 2017). Managers must pay particular attention to the training of end-users as well as to the other stakeholders that daily interact with the technology (Ahn & Kim, 2017). This approach reduces the internal resistance to change and provide professionals with the right skills to benefit from the technology (Barro & Davenport, 2019). Therefore, this study suggests that *access to technical skills* positively influences *perceived ease of use* as previously stated by Fan et al. (2020) and Balta-Ozkan et al. (2013). Furthermore, this investigation implies a polarization of customers' expectations towards AI which finds confirmation in the contributions of Cubric (2020) and Barro & Davenport (2019). As a result, customers are unable to balance the benefits and drawbacks of new technologies as predicted by Canhoto & Clear (2020) and Visser et al. (2020). Therefore, *customer awareness* positively influences both *perceived ease of use* and *perceived usefulness*.

As regards *lack of trust*, this study collected distinct findings that are in line with several articles identified in section 3. Firstly, this barrier negatively influences customers' *intentions to use* (Fan et al., 2020; Sanchez-Prieto et al., 2020; Luo et al., 2019) as well as *perceived usefulness* (Wu et al., 2011; Tung et al, 2008). Secondly, as recognised by several authors, customers establish trust based on how communication is handled and how transparent the development process is perceived (Visser et al., 2020; Körber et al., 2018; Hengstler et al., 2016). Lastly, results highlight how the presence of this barrier considerably determine the impact of *safety*, *security* and *job displacement* on the determinants of the TAM.

Within the healthcare industry, safety is not perceived as physical threat to human well-being, but it is rather a matter of transparency and representation (Złotowski et al., 2017). Professionals are afraid of not recognizing outliers and providing the wrong cure. The issues deriving from transparency involves failure transparency, judicial transparency and responsibility of the outcome as recognised by Dwivedi et al. (2021) and Arun et al. (2020). Nonetheless, when trust comes into play, professionals are willing to use the technology and learn from it. Therefore, this finding suggests that *lack of trust* and *safety* are strongly linked with each other and that in the absence of the first, *safety* becomes an important social barrier (Fernandes & Oliveira, 2021; Cubric, 2020; Złotowski et al., 2017; Hengstler et al., 2016).

As regards *security*, Gilbert et al. (2003) already described how trust takes an important part in determining the fear of cybersecurity attacks or data leaks. However, as stated by Wilson & Hash (2003), security awareness and training can be the leverage points to overcome this limitation. On one hand, awareness provides the customer with the necessary knowledge to be up to date on security practices and infrastructure (Wilson & Hash, 2003). On the other hand, training prepare companies in taking action once the cyberattack is happening. This result reveals once again, how *customer awareness* and *access to technical skills* can overcome the effect of other social barrier as in this case *security*.

Furthermore, the results from the interviews highlight two different perceptions from the two target groups. On one hand, customers recognised that AI increased the speed of digital automation, but it was not the cause of it (Dwivedi et al., 2021; Fleming, 2019; Jarrahi, 2018). On the other hand, the interviews with AI developers highlight the concerns of end users about developing new skills, adhering to KPIs, or losing their job as reported by Cubric (2020) and Ali & Rehman (2020). Therefore, *job displacement* is a barrier to end users' *intentions to use* in absence of trust towards the technology.

The findings of this study are consistent with the relationships of all six barriers previously identified except for the negative effects of *safety*, *security*, and *job displacement* on *perceived usefulness*. However, the interviews results highlighted two additional factors positively influencing *intentions to use*, namely *inefficient internal support* and *social pressure*. These two barriers are not novel to the technology adoption theories since the TPB, TAM2 and UTAUT already considered *internal support* (i.e., *facilitating conditions*) and *social pressure* (i.e., *subjective norms, social influence*). However, after a careful evaluation, the TAM was the most suitable theory supporting this study and therefore, the reason why these two determinants were not considered at the beginning. In Figure 13 is displayed the adapted model of this study based on the results of the interviews.

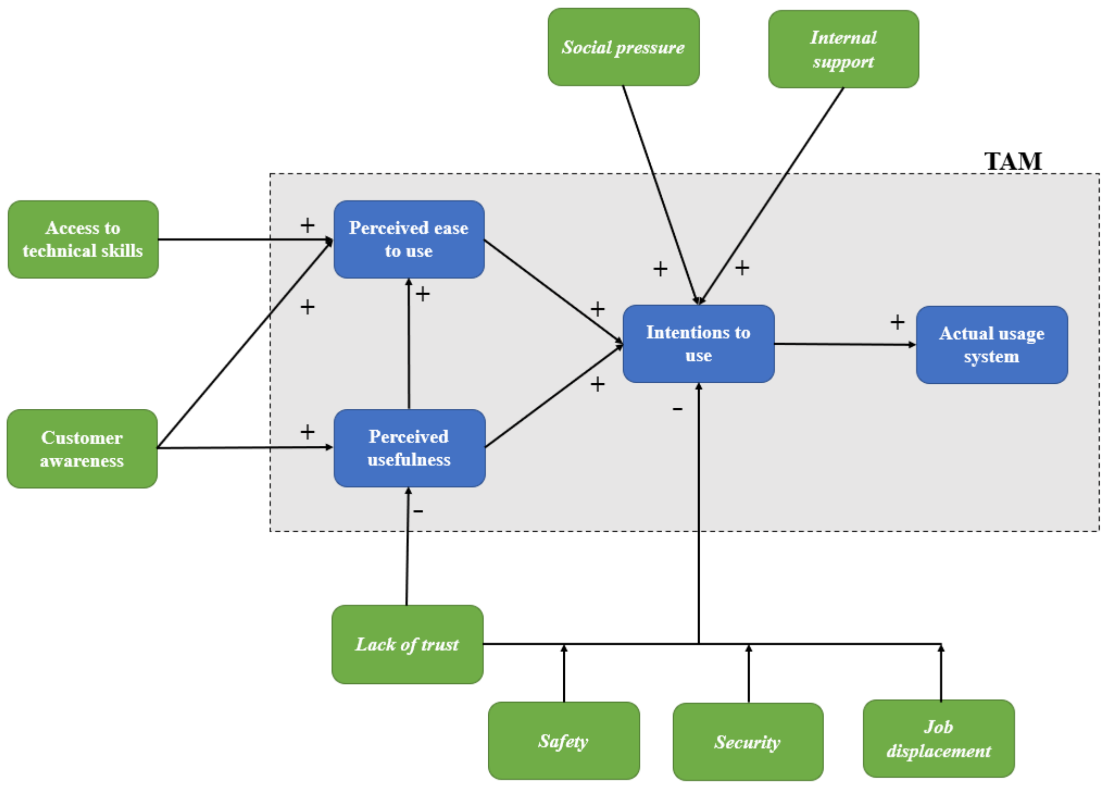


*Figure 13: The framework proposed by Marangunić & Granić (2015) (in blue) adapted accordingly to the effects of the eight social barriers confirmed by the interviews results (in green).*

In conclusion, there are eight social barriers that differently influence the *intentions to use* of customers. However, two of them have a positive effect on *perceived ease to use* and *perceived usefulness* which allow AIIC to counteract the negative effect of the others.

### *6.1.2 Qualifications to facilitate AI adoption*

According to the interviews, the 12 qualifications listed in section 5.2 are crucial for AI adoption. To start, these qualifications are clustered in three categories (see Appendix E in figure 22)*:*

(i) T*echnology-oriented domain* contains job profiles that are directly involved into the technical development of the technology (i.e., *data scientist, AI developer company*).

(ii) *Industry-oriented domain* includes people that are highly experienced or knowledgeable regarding a specific industry's field or activity (i.e., *experienced end users, hybrid profile, ethical expert, lawyer*).

(iii) *Data-oriented domain* consists of job profiles responsible for the data governance and data management of a company including its IT infrastructures and cybersecurity (i.e., *data steward, data custodian, data quality manager, business translator, analytic translator, data architects).*

The three domains described support those identified by Brock & Wangenheim (2019), namely strategy, technology, data, and security.

Relatively to the first cluster, the company's approach to AI adoption determines which qualification is necessary. The decision is between self-developing the technology or co-developing with another company. Generally, the more complex the AI solution, the stronger the need for advanced skills and resources (Raisch & Krakowski, 2021). Therefore, the technology-oriented qualifications are defined as:

*i)* *Data scientist:* individual with a multidisciplinary profile that combines computer science, statistics and mathematics (Costa & Santos, 2017; Dhar, 2013).

*ii)* *AI developer company:* organization that is specialize in the development of specific technology applications, or more in general, AI projects.

Next to this, interviewees also highlighted the importance of involving other profiles that are complementary to the development of the technology. These qualifications belong to the industry-oriented cluster and they are defined as:

*i)* *Industry expert – experienced end users:* the job profile of this person is strictly related to the AI application that the company desires to adopt. For example, if the solution applies to the radiology department, professionals as radiologists must be involved.

*ii)* *Hybrid profile*: this individual should have data-science skills as well as industry knowledge. However, the specificity of these skills in both domains should not be at the highest.

*iii)* *Ethical expert – business ethicist*[2]: this person should understand what AI entails, and which are its implications for the business and society. Therefore, this profile is highly knowledgeable in ethics and have some degrees of knowledge also in technology and the industry itself.

[2] Business ethicists are responsible for analysing the relationship and implications of technology between business, technology and society (Martin & Freeman, 2004).

*iv)* *Legal expert – lawyer:* this person is highly knowledgeable on the legal framework behind the technology which comprises its development, implementation and use.

Furthermore, AI developers encountered challenges related to the state-of-the-art of the customers' infrastructure and data which considerably hindered the adoption of AI. This finding support what stated by Sun & Medaglia (2019) which identified three data challenges that are commonly experienced during the implementation of AI, namely (i) data availability, (ii) data integration and (iii) data standards. It is in this scenario that the access to the qualifications of the third category is crucial. These profiles are defined as following:

i) *Data steward*[3] and *data custodian*[4]– these profiles should be able to clarify the available data and its characteristics as a company's asset. The data steward reports to the data custodian in terms of responsibilities and tasks.

*ii)* *Data quality manager* – To ensure quality, this person should identify, communicate, and assess data standards concerning accuracy, timeliness, completeness and credibility.

*iii)* *Business translators, analytics translators, data architects*[5] – these profiles should help AI developers to identify and later translate the company's business problem into the first step of the CRISP-DM methodology, namely business understanding. Next to this, data architects ensure the interpretability of the data.

All the qualifications listed are rather specific in the fields to which they apply. However, the same profiles could suggest knowledge and skills of the other two categories. A data scientist, for example, might specialize in the healthcare industry or have specific expertise of data management procedures. Therefore, the level of expertise of each profile is variable within the three categories.

Furthermore, the specificity of the competencies required is determined by the complexity of the solution as well as the industry in which the organization operates. In this context, the EU established a standard European Qualification Framework (EQF) with eight levels of expertise (Europass European Union, 2017). This framework is valid to any qualification across countries and institutions. The EQF begins with level one in which knowledge, skills and autonomy are at their basics. These three dimensions increase with each level until they reach level eight, representing the most advanced frontier of knowledge, skills, and autonomy in a field of job or study (Europass European Union, 2017). A more detailed representation of each level is provided in Appendix G in figure 26. Therefore, the level of expertise is a decisive requirement for the design of the

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[3] "*Asset data is managed by the data custodian on behalf of Company A. (…) They are also responsible for endorsing data management plan, endorsing data cleansing plan, ensuring data is fit for purpose*." (Cheong & Chang, 2007, p. 1005).

[4] *"Data Stewards have detail knowledge of the business process and data requirements. At the same time they also have good IT knowledge to be able to translate business requirements into technical requirements."* (Cheong & Chang, 2007, p. 1005).

[5] Data architects are responsible for "*establishing the semantics or 'content' of data so that it is interpretable by the users"* (Khatri & Brown, 2010).

framework since it provides information about what an individual is supposed to know, understand and be accountable for (Europass European Union, 2017).

## 6.2 AIIC approach to access to technical qualifications

The purpose of this first solution is to provide the AIIC and potential customers with guidance on which qualifications would facilitate and, as a result, accelerate the adoption of AI. In section 6.1.2, twelve potential profiles have competencies in three different disciplines, namely (i) t*echnology-oriented domain,* (ii) *industry-oriented domain* and (iii) d*ata-oriented domain.* In the following section, I explore the requirements necessary to design a solution for the AIIC.

### *6.2.1 Design requirements for accessing technical qualifications*

From the analysis in section 6.1.2, the solution must fulfil two requirements to achieve its purpose:

1. Display any presence of difficulties in accessing to certain profiles.
2. Include the level of expertise the individual must have to facilitate AI adoption.

Starting from the first requirement, four profiles require careful considerations. First, because of the expanding potential of this technology, the data scientist profile is in great demand in the market yet difficult to secure. Second, the hybrid profile is not yet recognized in the market by the interviewers. As a result, there is no pre-defined role that customers may currently access, but rather it must be crafted within the organization. However, there are pre-defined training programs that can help an end-user developing some technology-oriented competencies. Third, because AI adoption has not yet reached the mainstream market, it is difficult to identify lawyers or business ethicists specialized in AI within a distinct industry. In contrast, access to the six data-oriented qualifications is facilitated by the market's supply of professional services that assist organizations in establishing their data governance. This because data governance and management are considered a fundamental step for digital transformation (Khatri & Brown, 2010). However, if a company cannot afford these professional services, management may choose to recruit and rely on a single specialist in the field. Nonetheless, an individual's changing activity may not be sufficient for a short-term influence.

The second requirement appoints the presence of EQF for each role within each category. In fact, each profile is more competent in one of the three domains identified. However, this does not exclude that she/he might have knowledge, skills and autonomy in the remaining fields. Therefore, the proficiency of each profile is considered with the minimum EQF required in technology, industry and data-oriented competencies. Moreover, each rank already represents the three dimensions of the EQF, namely knowledge, skills, and autonomy. For example, “Individual A” is a data scientist which level of technology competencies is equal to 6. Looking at the EQF (Appendix G in figure 24), this person has advanced knowledge in AI with comprehensive skills to develop a creative solution. Furthermore, this individual demonstrates a level of autonomy that enables him or her to manage difficult and unpredictable situations. However, he/she also presents a level 5 in industry and level 7 in data-oriented competencies. Therefore, “Individual A” is a skilled data-scientist with a comprehensive understanding of the industry he/she is working and advanced data management skills. In Table 10 in appendix H, I propose a summary of this section by displaying the qualifications resulting from the interviews as well as the information concerning the two requirements.

Lastly, through this solution, AIIC will guide the customers to successfully approach AI projects also becoming a communication tool between AIIC and potential customers. As a result, to facilitate AIIC in presenting and explaining the framework, I must include a new requirement:

3. As a communication tool, the visualization of the solution must be clear, complete, and easy to understand.

### *6.2.2 Three approaches to access technical qualifications*

The AIIC can adopt a variety of techniques to guide potential customers in finding competent human resources. First, the AIIC could position itself as a private consultant and provide customers with access to the information highlighted in this report. As a result, the AIIC will communicate any difficulty in accessing certain AI qualifications and the level of expertise required. Besides, the presentation can easily structure to allow quick customers' understanding. However, the knowledge will stay private, and customers can access it only in exchange for an economic contribution. For this reason, the solution does not fit the vision of the AIIC and the business model. If the knowledge remains private, the AIIC cannot accelerate AI projects in the Region because its action will stay localized to certain customers.

Customers also require assistance in getting access to the qualifications they selected. Conversely, the AIIC's consultation will only provide access to knowledge. As a result, the AIIC could hire head-hunters as an add-on to the private service. Nonetheless, this solution requires substantial resources from the AIIC and the customers themselves. Besides, it still would not fit the vision and business model of the AIIC.

A third option is to design a clear framework that includes both difficult accesses and the level of expertise. The AIIC will use this framework as a communication tool with any stakeholders who contact the Centre. On the one hand, the AIIC can identify potential profiles within its network and connect them with customers. On the other hand, customers can recognize the importance of these qualifications and self-mobilize to obtain them. Therefore, the design of a framework that can be used as a public communication tool is the preferred approach that reflects both the vision of the AIIC and its business model (Table 4).

| **Requirements**<br>x = *“yes”* | **Private consultation:** | **Private hiring:** | **Public consultation & public action:** |
|---|---|---|---|
| 1. Display any presence of difficulties in accessing to certain profiles. | x | | **x** |
| 2. Include the level of expertise the individual must have to facilitate AI adoption. | x | x | **x** |
| 3. As a communication tool, the visualization of the solution must be clear, complete, and easy to understand. | x | | **x** |
| 4. The solution should fit the vision and business model of the AIIC. | | | **x** |

*Table 4: A comparison of different approaches that AIIC can adopt in relation to access to technical qualifications, namely (i) private consultation, (ii) private hiring and (iii) public consultation and public action.*

### *6.2.3 Proposals for AI qualification framework*

I propose two options of AI qualification frameworks. The first alternative is presented in figure 14. This option includes the twelve profiles identified together with their definition. Besides, it displays with a red dot whether these roles are difficult to access or not. Next to this, each profile is considered under the three discipline as well as their minimum EQF. Lastly, I included two examples of how to apply the framework with two hypothetical personas (i.e., “Individual A” and “Individual B”). The second option offers a similar perspective, but it particularly emphasizes the third requirement. In fact, the first choice accentuates the second requirement by showing the potential alternatives of EQF among profiles. However, it is not visually simple. Therefore, in figure 15 a more user-friendly alternative is proposed. This option displays the same characteristics as the first, namely the definitions of the twelve profiles, the presence of difficulties in accessing these qualifications (i.e., red dot) and the minimum EQF in each discipline. In addition, the framework displays the third dimension of the EQF, namely “Responsibility and autonomy”. This is because it provides an immediate grasp of what the individual is expected to be responsible for, avoiding confusion between knowledge and skills as already encountered during the interviews.

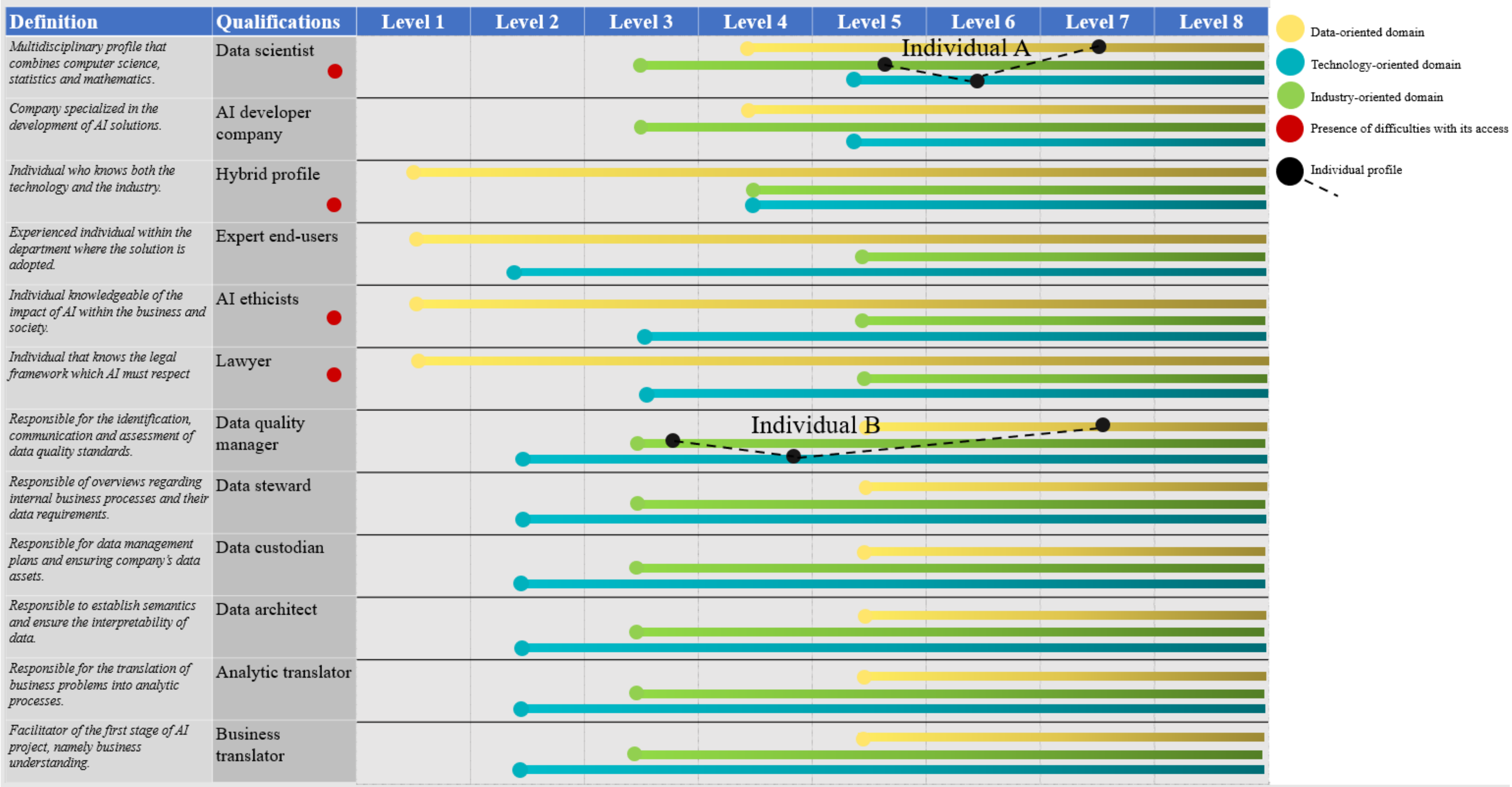


*Figure 14: The first proposal of the AI qualification framework offered in this study includes all the requirements identified (i.e. (i) presence of difficulties with access, (ii) proficiency level and (iii) clear visualization). It also offers two examples of application of this framework, namely "Individual A" and "Individual B".*

**Legend:**

- Data-oriented domain
- Technology-oriented domain
- Industry-oriented domain
- Presence of difficulties with its access

| | Responsibility and autonomy |
|---|---|
| | *Responsibility and autonomy is described as the ability of the learner to apply knowledge and skills autonomously and with responsibility.* |
| Level 1 | Work or study under direct supervision in a structured context. |
| Level 2 | Work or study under supervision with some autonomy. |
| Level 3 | Take responsibility for completion of tasks in work or study; adapt own behaviour to circumstances in solving problems. |
| Level 4 | Exercise self-management within the guidelines of work or study contexts that are usually predictable, but are subject to change; supervise the routine work of others, taking some responsibility for the evaluation and improvement of work or study activities. |
| Level 5 | Exercise management and supervision in contexts of work or study activities where there is unpredictable change; review and develop performance of self and others. |
| Level 6 | Manage complex technical or professional activities or projects, taking responsibility for decision-making in unpredictable work or study contexts; take responsibility for managing professional development of individuals and groups. |
| Level 7 | Manage and transform work or study contexts that are complex, unpredictable and require new strategic approaches; take responsibility for contributing to professional knowledge and practice and/or for reviewing the strategic performance of teams. |
| Level 8 | Demonstrate substantial authority, innovation, autonomy, scholarly and professional integrity and sustained commitment to the development of new ideas or processes at the forefront of work or study contexts including research. |

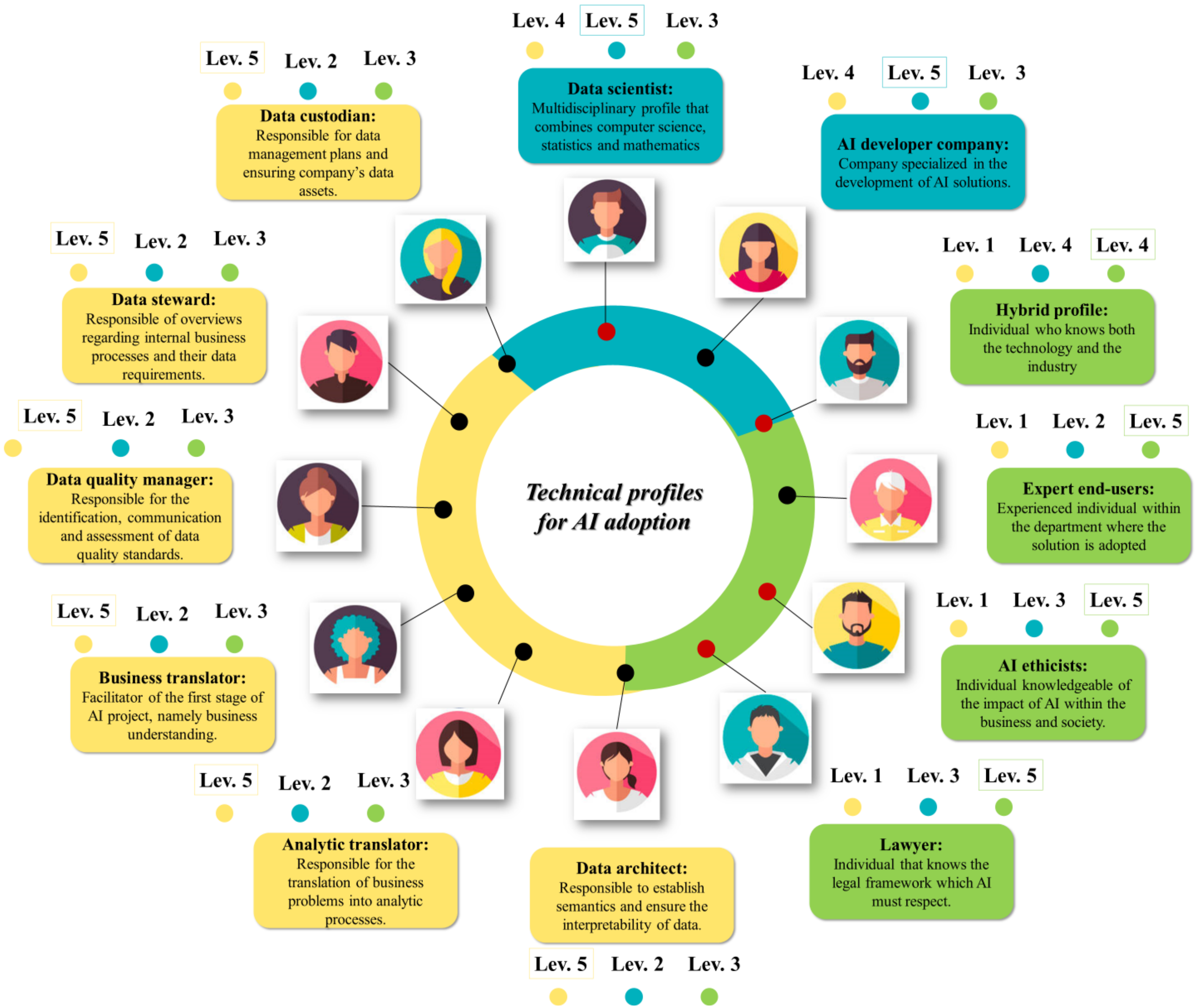


*Figure 15: The second proposal of the AI qualification framework offered in this study includes all the requirements identified (i.e. (i) presence of difficulties with access, (ii) proficiency level and (iii) clear visualization). However, it differentiates from the first one due to emphasis on the third requirement providing a more user-friendly visualization.*

However, as resulting from the analysis of the interviews with AI developers, access to distinct qualifications must happen before the adoption of AI. The qualifications within the data-oriented domain have the highest priority compared to industry and technology domains. Potential customers must undertake several steps to reach a level of data maturity that allows AI developers to deal exclusively with the complexity of the technology. Therefore, the first step towards an AI project from a customer point of view is to map the current situation in terms of data governance and management. Once responsibilities and processes are underlined, the company should also understand the state-of-the-art of their available data. By doing so, management should have a first impression of where their weaknesses are and therefore, their internal gaps. From then on, there are different approaches the company can choose, namely training existing employees, hiring new people or if affordable, access to professional services (section 3.3.2). Throughout this whole process of diagnosis, AIIC can facilitate access to expertise in digital transformation and help customers in this transition.

These steps do not facilitate only the first interaction with AI but also accelerate its adoption. Because of pre-adoption interceptions, the gap between customers and AI developers may be narrowed. If customers ensured these conditions, identifying the business problem and assessing the risks and benefits of the technology would be less challenging. Moreover, companies can decide between self-developing AI or approaching specialized organizations while investing in risk-management practices. The AIIC can ease access to these competences not only because of its position within its ecosystems, but also because of the community that actively supports the Centre's vision. Next to this, the AIIC can stimulate the creation of hybrid profiles in the short-term through the collaboration with the Centre of expertise in challenge-based learning, namely Tu/e Innovation Space (Tu/e Innovation Space, 2021). Through its community, AIIC can offer practical AI challenges in which students apply the knowledge and the coaching provided by Tu/e Innovation Space on real industry issues. By doing so, future candidates have acquaintance with both the technology and a specific industry. Next to this, Tu/e Innovation Space is part of the Dutch educational ecosystem. Therefore, a long-term plan for the integration of a hybrid curricula can be developed in collaboration with the AIIC.

Lastly, on not all occasions AI ethicists or lawyers are necessary. Sometimes the integration of the technology within the company and the society only requires investments in effective change management practices. Because of his extensive expertise in the sector, one of the AIIC's founders is considered a specialist in the subject of change management. Therefore, the AIIC can help potential customers in addressing this challenge through its network or a direct professional service. In figure 16 I provided a timeline that visualizes where AIIC can intervene to accelerate AI project in the Brainport Eindhoven region.

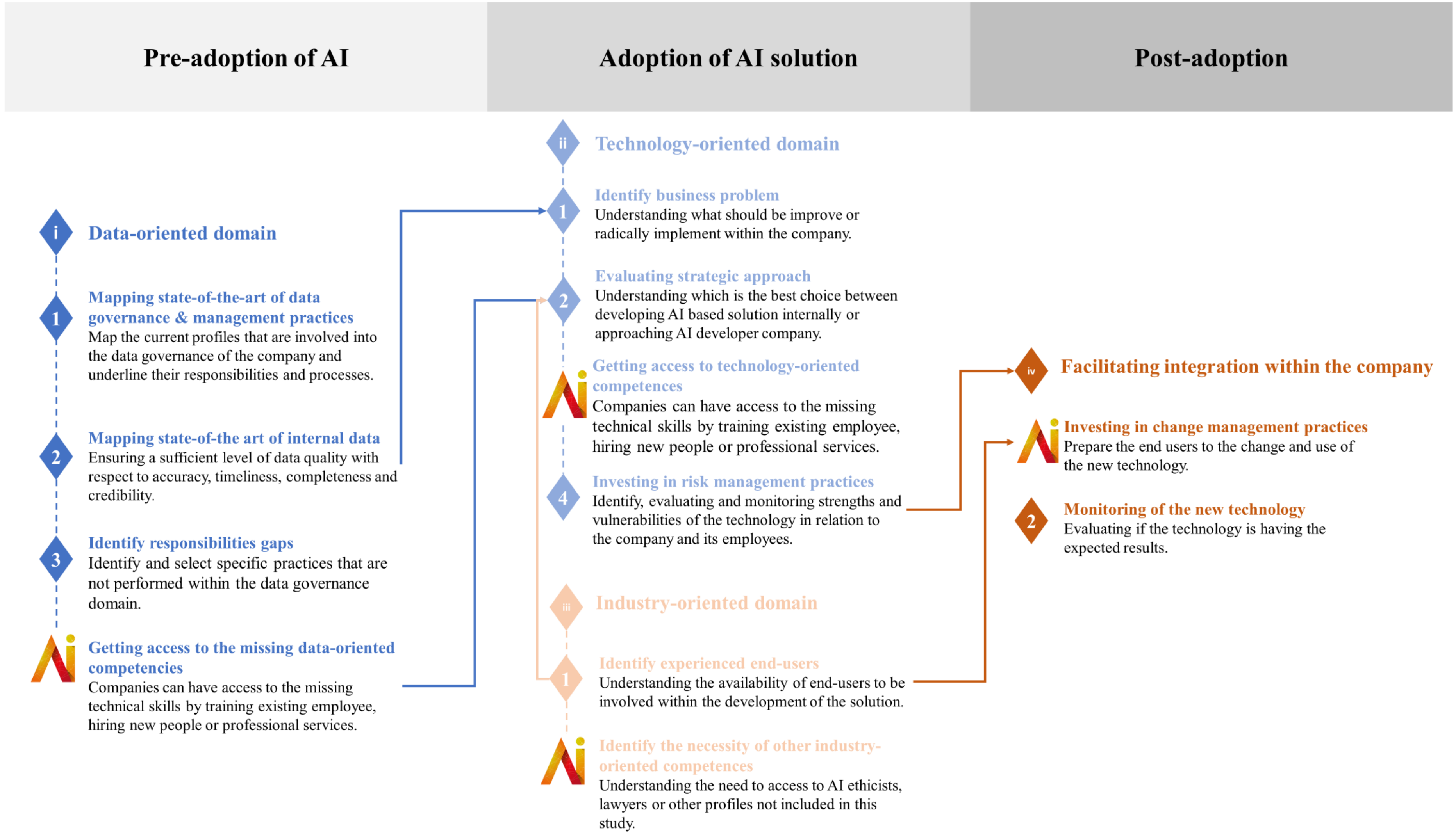


*Figure 16: The timeline of AIIC intervention related to access to technical qualifications which develops in three staged of adoption, namely (i) pre-adoption, (ii) adoption and (iii) post-adoption.*

## 6.3 AIIC approach to customer education

In the light of the results collected, the AIIC can directly impact the acceleration of AI project by educating potential customers in relation to the fundamentals of the technology which according to this study is rather lacking in the market. In the following section, I collected all the requirements that the second solution proposed should respect to be successfully implemented within the AIIC's business model.

### *6.3.1 Design requirements to customer education*

This solution must fulfil a variety of requirements established in different stages of this study. First, there are four theoretical requisites according to the literature (section 3.3.1):

1. The SECI model should be the foundation of the solution.
2. The presentation of use cases must demonstrate transparency within their development (Hengstler et al., 2016).
3. The solution should follow the guidelines of the *ba* during the first stage of the SECI model, namely socialization.
4. The solution must involve the management of the company as first target group (Barro & Davenport, 2019).

Second, the results of the interviews highlighted multiple suggestions useful to identify the content of the information (Appendix E Figure 25):

5. The solution should communicate the steps the customer must consider before adopting AI (e.g., updating IT infrastructure, check the availability of data and ensure data quality).
6. The solution should distinguish different industries and the relative content in each of them.
7. The solution should educate the customer in relation to the definition of AI, its benefits, its limitations and where possible, the influence on the employees' performances.
8. Showcasing use cases within the market is essential (and maybe experiences).
9. The solution should emphasize how the technology is developed and encourage customers in approaching AI with an experimental attitude.

Lastly, through the interviews with the founders of the AIIC, I identify several requirements that would help the solution to be successfully implemented within the AIIC business model:

10. Quantify the contribution within the AIIC vision (short and long term)
11. The solution should fit the current business model of the AIIC
12. Defining the progress of the participants
13. The management must be personally invited, but also other people within the company can participate
14. Roadmap of the steps that AIIC, customers and developers must take within the solution
15. Modular structure to ensure flexibility
16. AIIC will be the organizer of business cases

### *6.3.2 Three approaches to customer education*

There are three different approaches that the AIIC can adopt to customer education. First, the Centre can set up a Massive Online Open Course (MOOC). This solution provides the customers with fundamental information about the technology, use cases, and modular flexibility. Furthermore, the MOOC would first target management, and their progress could be tracked across several modules. However, the MOOC meets only partially the first and third requirements. The socialization step of the SECI model and the resulting community (i.e., *ba*) is more effective when people share similar experiences and physical space. Next to this, to allow scalability online courses usually are pre-recorded and open discussions among participants are not always possible. This is a crucial disadvantage especially when use cases are presented. People have numerous questions regarding the projects and how they developed. Offline events boost discussions and encourage interactions among attendees which are crucial to stimulate knowledge sharing. As a result, the MOOC is not a perfect match with what the AIIC is trying to achieve.

To solve the MOOC's shortfalls, the second option for the AIIC is to organize an offline demonstration event. In this way, people can interact with each other once the use cases are presented. From the results of the analysis in chapter 5, showcasing is crucial to overcome an initial distrust towards the technology. However, emphasizing only use cases is not a viable option. The main goal of the AIIC concerning customer education is demystifying AI and providing the customer with the fundamental information that the market is currently lacking. Therefore, the informative content of the event would not be adequate to sufficiently prepare customers on AI adoption and the steps required.

However, these two alternatives are complementary to each other. Therefore, a third option that merges the strengths of informative courses and showcasing is the Customer Awareness Program (CAP). The CAP is a collection of workshops that are offered by the AIIC to provide customers with information about the technology's benefits, limitations, and business cases. The Program is divided into three informative modules which are kicked off by use cases presentations. After each module, the Centre will facilitate open discussions and stimulate interactions among attendees. As a result, the CAP is the solution that meets the highest number of requirements and better fits the vision of the AIIC. Table 5 offers a detailed comparison of the three solutions. Following that, the next section delves into the structure and content of the CAP in further depth.

| **Requirements**<br>x = *"yes"*<br>/ = *"partially"* | **Massive Open Online Course (MOOC)** | **Demonstration event** | **Customer Awareness Program (CAP)** |
|---|---|---|---|
| 1. The SECI model should be the foundation of the solution. | / | x | **x** |
| 2. The presentation of use cases must demonstrate transparency within their development (Hengstler et al., 2016). | | x | **x** |
| 3. The solution should follow the guidelines of the *ba* during the first stage of the SECI model, namely socialization. | / | x | **x** |
| 4. The solution must involve the management of the company as first target group (Barro & Davenport, 2019). | x | x | **x** |

| **Requirements**<br>x = *"yes"*<br>/ = *"partially"* | **Massive Open Online Course (MOOC)** | **Demonstration event** | **Customer Awareness Program (CAP)** |
|---|---|---|---|
| 5. The solution should communicate the steps the customer must consider before adopting AI (e.g., updating IT infrastructure, check the availability of data and ensure data quality). | x | | **x** |
| 6. The solution should distinguish different industries and the relative content in each of them. | x | x | **x** |
| 7. The solution should educate the customer in relation to the definition of AI, its benefits, its limitations and where possible, the influence on the employees' performances. | x | | **x** |
| 8. Showcasing use cases within the market is essential (and maybe experiences). | x | x | **x** |
| 9. The solution should emphasize how the technology is developed and encourage customers in approaching AI with an experimental attitude. | x | x | **x** |
| 10. Quantify the contribution within the AIIC vision (short and long term) | / | / | **/** |
| 11. The solution should fit the current business model of the AIIC | x | x | **x** |
| 12. Defining the progress of the participants | x | | **/** |
| 13. The management must be personally invited, but also other people within the company can participate | x | x | **x** |
| 14. Roadmap of the steps that AIIC, customers and developers must take within the solution | x | | **x** |
| 15. Modular structure to ensure flexibility | x | x | **x** |
| 16. AIIC will be the organizer of business cases | x | x | **x** |

*Table 5: A comparison of different approaches that AIIC can adopt in relation to customer education, namely (i) MOOC, (ii) demonstration event or (iii) CAP.*

### *6.3.3 Proposal for the Customer Awareness Program (CAP)*

The CAP aims at creating awareness around AI by stimulating knowledge creation and sharing among potential customers. Each quartile, a new version of the CAP takes place for a different industry. As a result, the AIIC obtains three strategic advantages. First, it enables the Centre to reach out to a broader audience with targeted information (requirement 6). Second, the people to contact after each quartile are different, avoiding saturation in the short term. Third, if the Program is advertised as a once in a year opportunity for that industry, it provides a point of differentiation. Moreover, the CAP based its foundations on the four stages of the SECI model. First, "Socialisation" based its principles on people sharing the same experience and environment. Next to this, the AIIC creates a *ba* around the CAP which follows three conditions (section 3.3.1, p.44):

1. *Physical space* – the CAP takes place at the AIIC located at HTC in the building HTC 5.
2. *Selection of people involved* – the AIIC personally invites the first target group of the CAP, which is management. However, each manager has two open invitations that can be shared with other two colleagues. In this way, both requirements (4) and (13) are fulfilled.

3. *No boundaries conditions to join or leave* – at the time of registration, each participant can choose whatever module(s) he or she wishes to join.

By doing so, within the socialisation step, the CAP respects also requirements (1) and (3) with regards to the guidelines of the SECI model and the creation of a *ba* (Figure 17).

The second stage of the SECI model is “Externalisation” which aims at content creation. The Program consists of three modules that explore different aspects of the technology. Each module lasts around two hours and it takes place one evening of a different month within the quartile. By doing so, the Program is modular and grants the AIIC the flexibility to organize the content and schedule the session accordingly. Furthermore, because the primary target group is management, workshops during working hours are frequently not an option due to a lack of time. These decisions were made in response to criteria (15) and (16), in which AIIC founders emphasized their desire for a modular program where AIIC is the organizer.

The third step of the SECI model is to summarize the information given during the workshops to facilitate the last stage, namely internalization. In this regard, the AIIC is responsible for the creation of two types of flyers.

a. *Module 1:* no flyer needed - the first module is centred on letting participants creating a shared understanding of the industry applications through a brainstorming activity. Therefore, the content of this session highly depends on its outcome.
b. *Module 2:* Flyer 1 – a flyer with the summary of the benefits & limitations of AI within the industry and the learning points from the two use cases presented.
c. *Module 3*: Flyer 2 –a flyer with the contact points of the AI developers who joined the “Pitch rounds” and the “To-Do Steps” for a successful digital transformation.

In the last stage, the AIIC has no control over the participants’ capabilities to absorb the information shared. It is difficult to understand the progress of the members of the CAP since their participation is not granted in all three modules. As a result, condition (12) is partially met. Nonetheless, the AIIC can organize a follow-up action after each event:

1. *LinkedIn post*: follow-up social media post with the picture of the event, the tags of the participants, and the link to the videos shared during the session. As a result, the CAP's social promotion is boosted by its participants and the material of each session is available at any time.
2. *Follow-up email*: personal follow-up email to the attendees with attached a small questionnaire to understand the participants’ satisfaction, improvement points, and self-knowledge assessment. An example of a questionnaire is provided in Appendix I.

Thus, although AIIC cannot measure the internalisation step, the Centre can ensure a double-side communication with the participants. A summary of this section is provided in Figure 17 with respect to requirement 14.

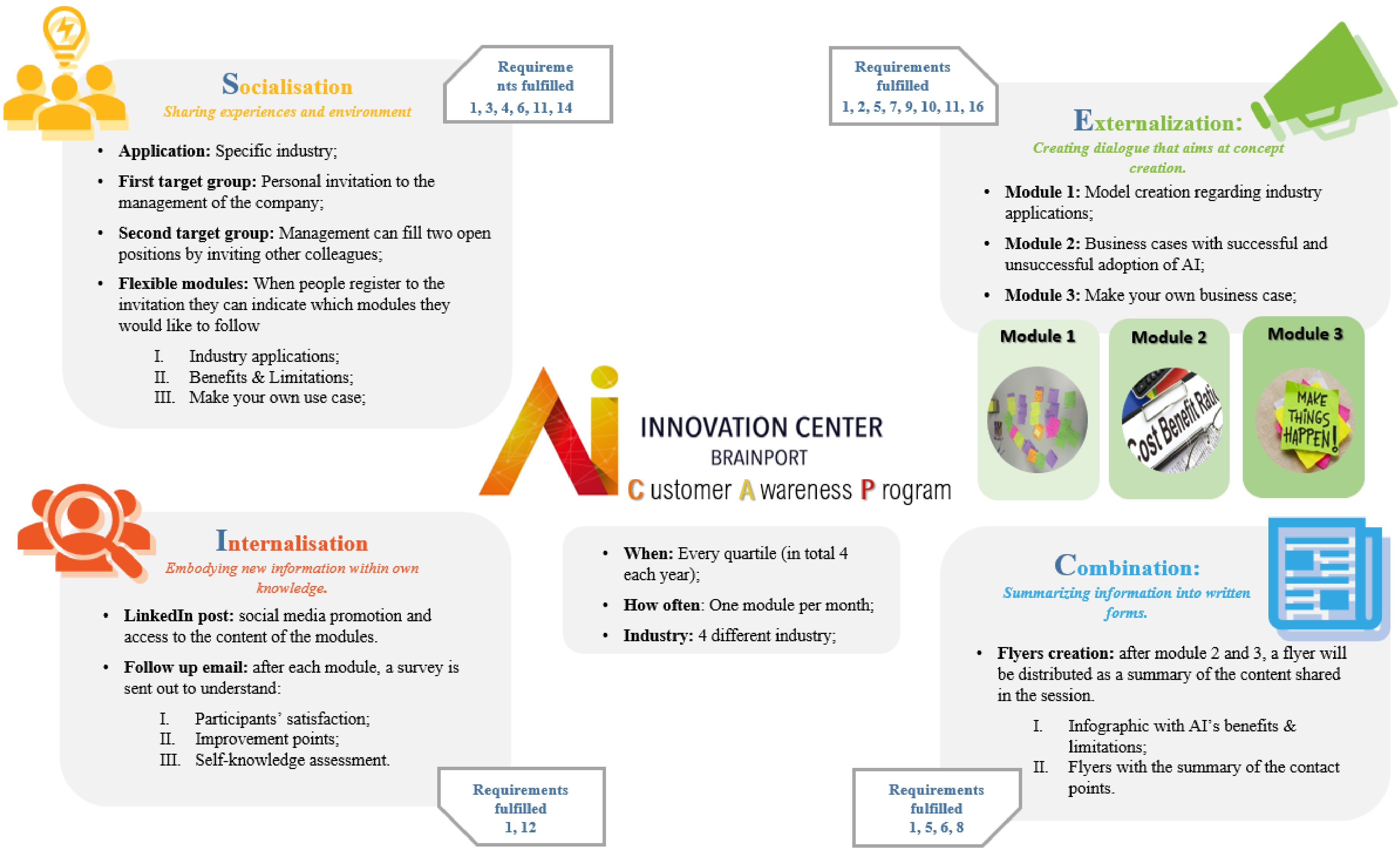


*Figure 17: The CAP foundations on the SECI model including the requirements that will be fulfilled in each step.*

Relatively to the content of the CAP, the three modules cover the fundamental aspects of the technology within a specific industry. The material provided during the CAP is created by the AIIC community and organized by the AIIC itself. This allows the CAP to be integrated into the AIIC's business model and the community that surrounds it (requirement 11). Next to this, by involving the members of the community, the AIIC offers the possibility to contribute to the circles' goal giving them a channel to test their material and ideas.

The first module named "Industry applications" helps participants in contextualising AI within their environment, visualizing the purpose of the technology and its potential performance. By doing so, the Centre stimulates initial trust towards the technology by presenting its potential opportunities (section 3.1.7). This module is composed by fours sub-sections of 30 minutes each (Figure 18):

1. *Introduction rounds*: the AIIC presents itself and the purpose of the CAP. Next to this, the content creators introduce themselves to the participants of the program.

2. *Introduction to AI and its applications*: this section starts with an elevator pitch of what AI entails. Afterward, participants form groups composed of 4/5 people in which attendees belonging to the same company stay together. Once the groups are ready, the AIIC provides post-its and a whiteboard with two questions: (i) "where do I potentially see AI in my industry?" and (ii) "where do I potentially see AI in my company?". Any access to phones or laptops is allowed. In this way, participants can engage in small research on the potential application of AI.
3. *Presentation of results & open discussion*: each group presents its results and experience. This moment is crucial for the AIIC because it establishes the topics for the open discussion. In this study, some of the interviewees were not able to recognize potential applications within their industry or company. Therefore, the AIIC should be prepared for this scenario and stimulate the discussion from those who presented some experience.
4. *Application within Brainport Eindhoven region & use case presentation:* the community of AIIC or the team itself can collect some use cases in the region and present them in a short video. Next to this, one representative of a use case can share the experience with the attendees.

The benefits and limitations of the technology are the subjects of interest in the second module of the program. The goal of this unit is to engage the audience with short videos and sharing experiences. This module is composed of three sub-sections of 30 minutes each (Figure 18):

1. *Introduction rounds*: presentation of the AIIC, CAP, and the community contributors. In this way, the new attendees also understand the vision of the AIIC and the purpose of the CAP.

2. *Pitch on AI benefits & successful use case:* this part starts with a pitch regarding the advantages of AI in the sector, with a focus on specific applications if possible. In addition, a company that has effectively adopted AI into its business can present its experience and key takeaways (requirement 7).

3. *Pitch on AI limitations & unsuccessful use case:* this part opens with a pitch about the limitations of AI. In addition, a company share its experience with the technology, including the pitfalls and the learning points during the implementation (requirement 7).

Lastly, the goal of the third module is to let customers interact with AI developers and take actions towards the adoption. This module focused on requirement 9, which specifies that the CAP should enable customers to understand how technology is developed and to approach it with a trial-and-error mindset. Therefore, this session is composed by two subsections of 30 minutes and the last one of 60 minutes (Figure 18):

1. *Introduction rounds*: presentation of the AIIC, CAP, and the community contributors. Next to this, the circle "*digital transformation"* can prepare a short pitch on what digital transformation entails, the steps to follow for a successful digital transformation, and the possible contacts (requirement 5).
2. *Pitch rounds:* AI developers or independent professionals can pitch their company and solutions. In this way, customers have an idea of what is possible within the Brainport region and who they can contact for more information.
3. *Networking:* the AIIC hosts a networking session in which AI developers and potential customers can personally meet.

To respect requirement 14, Figure 18 summarizes the contribution expected from AIIC at each step.

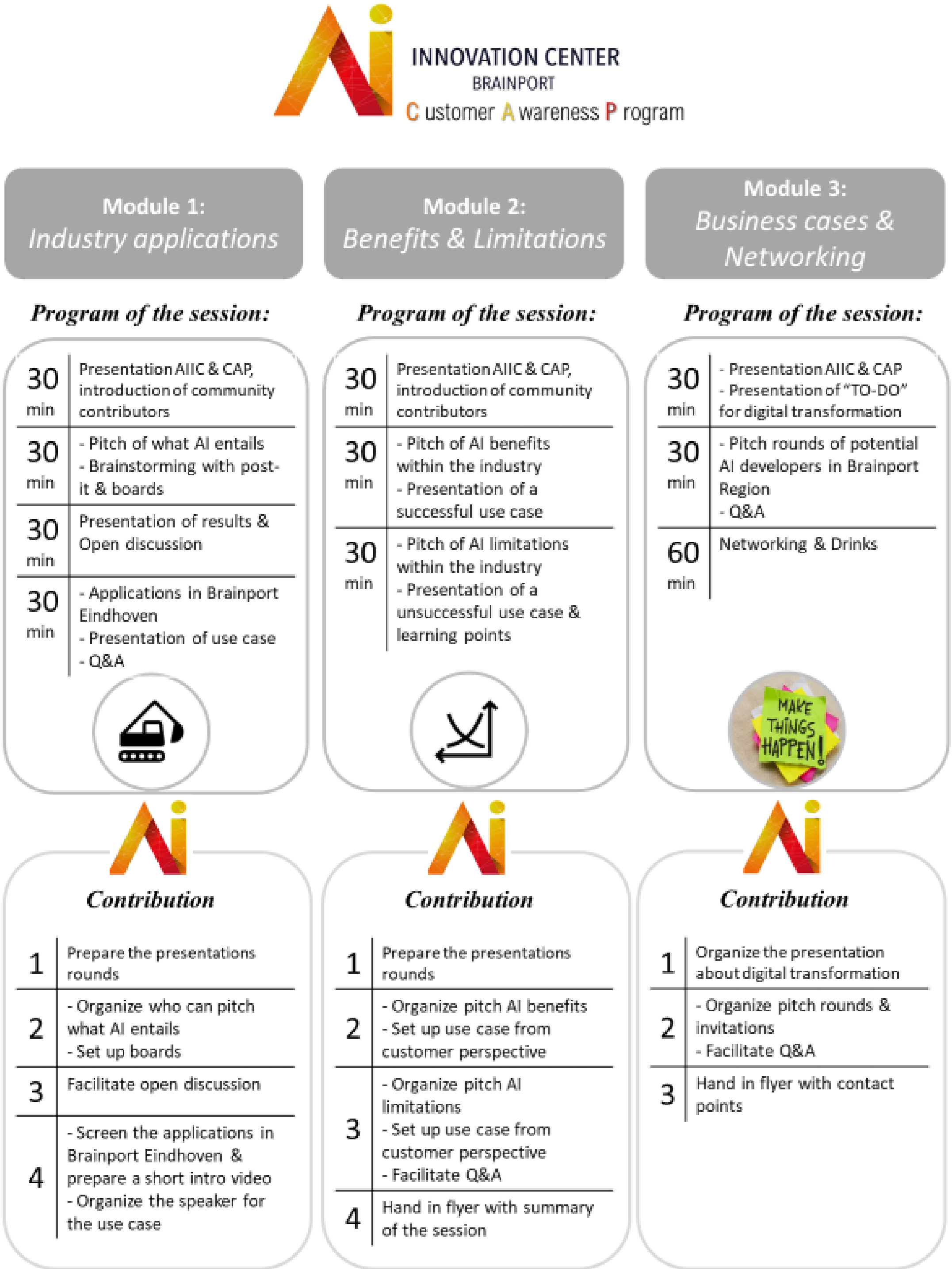


*Figure 18: The Customer Awareness Program consists of three modules (i.e., Industry applications, benefits & limitations, business cases & networking) in which the AIIC contribution varies accordingly.*

As a result, the CAP is highly centred on sharing best practices and use cases within each module (requirement 8). According to the second design criteria, the presentation of the use cases should guarantee transparency along the development process. However, since the content of the presentation depends on the use cases that AIIC provides, the Centre must emphasize this requirement once the company agrees in sharing its experience.

On the one hand, providing so many use cases allow AIIC to take advantage of its position as a facilitator within the Brainport Eindhoven region. The market is demanding for demonstrations to better comprehend the technology, and AI developers are increasingly using it as a sales tool. On the other hand, for the four variants of the CAP, the availability of use cases can be a bottleneck. The AIIC has not yet establish itself in the region. As a result, unless the AIIC offers a higher value exchange, companies are not willing to share their use cases with potential competitors. However, AIIC already benefits from the fact that it has five significant partners. First, these businesses are experimenting with AI while also advertising it at various events. Thus, they could be the CAP's first use cases to be disclosed. Second, HTC's culture is centred on open innovation, which reflects among the residents. Thus, the AIIC can use it to persuade companies in sharing their experiences.

However, the more established the AIIC becomes in the region, the easier it will be to find new use. As a result, the contribution of the CAP within the AIIC vision in the short-term is rather consistent:

1. *Targeted audience for AIIC circles:* the Program involves the member of the community and provides them with a channel to experiment their material and reach different audience.
2. *Impact makers:* through the CAP circles as *"digital transformation"* can pursue their goal of making an impact within the Brainport Eindhoven region.
3. *Targeted actions & information*: the CAP captures the information needs of the participants by offering four versions of the program each one specialized on a specific industry.
4. *Build initial trust towards AI*: through the content of the CAP, participants will receive fundamental information that allow them to contextualize the technology, identify its performances and understand who to contact in case of actions (section 3.1.7).
5. *Facilitate interactions within the network*: the Program offers the opportunity for AI developers, professionals or AI enthusiasts to meet potential customers and interact with each other.
6. *Extend AIIC network*: through social media promotion and personal tag of the attendees, the CAP can reach a broader network and extend its impact also outside the Region.

However, the long-term contribution is rather difficult to quantify. On one hand, the Program provides to potential customers with the fundamental information about the technology and what is currently happening in the region. In this way, the Program builds the fundamentals for trust and allows participants to take informed investment decisions. On the other hand, the AIIC aims at accelerating the industrialization of AI in the Brainport Eindhoven region. However, since AIIC is not a developer itself, it will be difficult to track the projects or partnerships that will start after the Program. Therefore, the quantification of long-term contribution of the CAP depends on the approach that AIIC adopts towards the participants once the Program ends.

# 7. Focus group

The focus group aims at validating the two solutions designed within the AIIC's business model. Therefore, the primary goals of this focus group are to determine whether the AIIC can integrate the solutions suggested, how they can be used effectively, and whether the Center has the resources to provide them.

## 7.1 Set-up of focus group

The focus group is one hour session in which I interacted with the AIIC team regarding different aspects of the solutions designed. The four participants are different in terms of knowledge and responsibilities:

- *Member 1 - Founder:* Initiator of the AIIC with experience in marketing and communication.
- *Member 2 - Founder:* Business developer & innovation manager of the AIIC with expertise in digital transformation, change management and agile project management.
- *Member 3 - Community manager:* Manager of relations and communications with the community of the AIIC with experience in marketing, events management, and public relations.
- *Member 4 - Marketing manager:* Manager of the marketing content related to AIIC & HTC with experience in marketing, USI expert, entrepreneurship, and start-up development.

Three days before the focus group, I shared with the participants the information contained in chapter 6 and asked them to read the material in advance and write down their questions and feedback. Due to the limited time of the session, this was crucial to ensure efficiency during the discussion and collect targeted feedback. Next to this, I communicated the program of the session which was structured as follow:

- *Part I (10 minutes):* Quick introduction to the AI qualification framework.
- *Part II (20 minutes):* Decision regarding which alternative to adopt, feedback & questions related to that alternative.
- *Part III (10 minutes):* Quick introduction to the Customer Awareness Program (CAP).
- *Part IV (20 minutes):* Feedback on the structure of the CAP and the contribution expected from the AIIC.

To facilitate Part II and Part IV, I prepared some questions as guidelines for the discussion which are available in Appendix J.

## 7.2 Final design of the AIIC approach

During the focus group I collected the feedback from all the participants. In the next section, I improved the solutions proposed according to the information and discussion shared during the session.

### *7.2.1 Final AI qualification framework*

The AI qualification framework received feedback regarding three distinct areas. First, the actual use of this framework within the business model of the AIIC was unclear to participants. Conversely, one of the goals of the focus group was to identify its possible applications. Therefore, following a brief debate, the members decided on two areas of action: education and awareness-raising.

1. *Education:* The framework is critical for the AIIC to select possible partners that can provide those qualifications and training courses to develop the specific skills. Especially the latter can constitute a potential revenue source for the Centre.

2. *Raising awareness:* The framework can be used by the AIIC to raise awareness on the steps a customer needs to take to successfully approach AI. As a result, the Centre can assist customers in identifying their human capital shortfalls and developing a strategy to address them.

The second point of discussion was the specific design of the framework. On one hand, the participants identified the second proposal as the most suitable communication tool. However, the team also suggested the integration of the two alternatives into a unique one. Therefore, in Figure 27 in appendix K, I provided a new visualization concerning the two proposals. In addition, the group discovered a major flaw: there was no indication of the time or priority in obtaining the twelve qualifications. After some follow-up questions, we concluded that the new proposal should integrate the elements of the roadmap provided in Figure 16 (section 6.2.3). Thus, the final version of the AI qualification framework is represented in the poster in appendix K in figure 28, which includes all the improvements suggested during the focus group.

Furthermore, the AIIC community was the last point of discussion on the AI qualification framework. The questions raised was "*How can we include the community around the Center in this tool?*". The answer is clear: the AIIC should profile community members and determine whether the qualifications proposed are already represented in the community. Next to this, within the community there might be potential partners that can help in accessing to those qualifications (e.g., head-hunters, HR companies, consultancy). However, the Center started very recently in this profiling activity. Therefore, this information is not yet available unless the AIIC asks directly to the members.

### *7.2.2 Final Customer Awareness Program*

The participants of the focus group provided input on the CAP's content and structure. In addition, the implementation of the Program within AIIC's business model has been examined. First, the Program will no longer take place over three months of a quartile, instead, a whole day will be dedicated to raising AI awareness. Therefore, module 1 will kick off the program, followed by module 2 after lunch, and module 3 as a closing activity. This choice reflects the AIIC's desire to keep the Program open and not limit it to management as the primary audience. The AIIC team particularly highlighted front-runners as ideal participants. However, after a follow-up discussion, the team did not have sufficient information on how to identify these profiles within customers' companies. Therefore, the marketing campaign will aim at reaching as many people as possible rather than personally inviting the management of the companies. Furthermore, participants can still indicate which module(s) they want to join. However, the choices will be between joining all the modules (i.e., whole day) or only modules 2 and 3 (i.e., half-day). This allows a consistent number of attendees during the whole event.

In light of these decisions, I revised the program of the CAP. First, the introductory session of module 1 is sufficient also for the next modules. Second, the AIIC team recommended incorporating simulations or demos where attendees can try out the technology. As a result, the first subsection of module 2 is dedicated to AI simulations. In module 3, after the presentation by the digital transformation circle, the AIIC will facilitate an open discussion concerning the topics presented. Thus, the final proposal of the CAP is available in appendix K in figure 29 and 30.

Furthermore, I questioned the attendees regarding the integration of the CAP within the AIIC's business model. On one hand, the group unanimously recognised the potential of the Program and agreed on the support that such a tool could give in demystifying AI. On the other hand, the group raised three fundamental questions:

1. *"Where does the CAP drive?"*
2. *"How do the two tools tight together?"*
3. *"What should we do for the actual implementation?"*

The first question is related to the long-term impact of the CAP. As mentioned before, the quantification of the CAP's contribution within certain KPIs depends upon the follow-up approach that the AIIC desires to adopt. However, the general benefits of such a Program are several. First, raising awareness allows customers to create confidence towards the technology and overcome initial distrust. Second, the Program allows self-mobilization and knowledge sharing. The net result is a positive perception of the technology which fosters informed investment decisions and promotes technological advancements.

In the second question, the group tried to identify a common approach between the two tools presented. On the one hand, the AI qualification framework and CAP are distinct solutions that represent two different constructs, namely *access to technical skills* and *customer awareness*. On the other hand, the framework also aims at raising awareness. As a result, it can be integrated and presented in the third module of the CAP. However, in this study, the two solutions are considered as distinct outcomes.

Lastly, a clear answer to the third question is to approach the implementation of the CAP with a trial-and-error mindset. The AIIC team can collect feedback after each Program and carefully implement it in the next version. The flexibility granted by the CAP allows improvements to be quickly combined. Besides, further recommendations based on the results of this study are provided in the next section.

# 8. Conclusion

Artificial Intelligence (AI) is a cutting-edge technology that, while a few years ago it was at its peak of inflated expectations, it is now facing significant obstacles. It is in this scenario that the AIIC decided to support the industrialization of the technology in Brainport Eindhoven region. This study through a qualitative analysis, identifies which social barriers are challenging the adoption of this technology. Next to this, it proposes two solutions that stimulate customers' intention to use and overcome initial distrust.

In the following section, I respond to the research question that frames this investigation. Moreover, I identified the theoretical contributions as well as the managerial recommendations. To conclude, I selected the main limitations and future research suggestions that this study offers.

## 8.1 Answer to research question

The research question that leads this study is: "*How can the AI Innovation Centre help accelerate AI technology projects by providing customers access to technical skills and information to overcome their social barriers?*". To answer this question, I first identified how to stimulate technology adoption and how the model applies to AI. As a result, I selected the TAM as the most suitable model to represent AI adoption which identifies *perceived ease to use* and *perceived usefulness* as potential drivers. Next to this, literature recognized the presence of common social barriers, namely *customer awareness, access to technical skills, lack of trust, safety, security,* and *job displacement.* By applying the TAM to AI adoption, I proposed a model that included these obstacles and suggested *customer awareness* and *lack of technical skills* as potential leverage points to overcome the negative effect of *lack of trust, safety, security,* and *job displacement*. The last four barriers indeed presented a negative impact on AI adoption mostly dictated by the presence or absence of trust.

Secondly, the next goal was to determine best practices to stimulate awareness and facilitate access to technical skills. The SECI model was identified in the literature as one of the most influential frameworks to explore knowledge creation beyond organizational boundaries (Baldé et al., 2018; Nonaka et al., 2000). Therefore, after an analysis of its guidelines and applications, I decided that the SECI model would be the foundation for the AIIC approach to customer education. Next to this, considering the position and resources of the AIIC, I suggested that being part of the innovation ecosystem of HTC, or even broader the entrepreneurship ecosystem of Brainport Eindhoven Region, allows the Centre to connect customers with key players. Next to this, the AIIC already created a community where professionals that share a passion for AI or the same vision of the Centre, can help customers in adopting AI. Therefore, in the first part of my study I identified what stimulates adoption and the best practices to make it successful.

However, literature did not reach a consensus regarding which social barriers hinder AI adoption and neither which skills nor information the market needed. As a result, the second half of my research focused on validating these obstacles and determining the content of my proposed solutions. Through a qualitative analysis, I validated the six social barriers previously selected. Besides, two new obstacles were considered, namely *internal support* and *social pressure.* These determinants were not new to the adoption theories, but they were discarded once the TAM was chosen. Next to this, the results of the interviews showed that the market is polarized under different perspectives. First, AI developers expected the customers to already engage in data governance and management practices. However, customers considered AI developers as the guides along the process without proactively engaging into AI adoption. Second, customers presented a polarization of their expectations towards the technology being either too positive or negative. Third, potential customers were not able to identify specific skills that would help AI adoption. Nonetheless, AI developers described twelve job profiles that would fulfil the goal. Besides, customers lacked basic knowledge about the technology's benefits, limits, and contextualization. As a result, the purpose of the technology was misunderstood encouraging initial distrust.

In light of these results, I considered several approaches the AIIC could adopt concerning awareness creation and access to technical skills (section 6.2.2 and 6.3.2). After a careful evaluation, I selected two tools that answer the research question, namely the AI qualification framework and the CAP. First, the AI qualification framework guides the AIIC through its role of facilitator in getting access to technical skills. Next to this, the tool allows the Centre to identify training opportunities and partnerships within its network. Besides, by introducing the framework to the customer, the AIIC helps companies in identifying their human capital shortfalls. According to the TAM, all these actions positively impact the customers' *perceived ease of use* and in turn, their *intentions to use*. Conversely, the CAP directly aims at providing customers with fundamental information about the technology, use cases, and contacts within the Region. This Program allows customers to get familiar with the technology and overcome initial distrust. As mentioned before, the absence of trust considerably affects the impact of *safety, security,* and *job displacement.* Thus, by overcoming initial distrust the effect of the other barriers is less effective. Next to this, the Program promotes self-mobilization and knowledge sharing. Participants are encouraged to interact with each other and share the vision of the Centre. By doing so, also the other two determinants *social pressure* and *internal support* are stimulated. Thus, the AI qualification framework and the CAP are recognized in this study as the solutions to accelerate AI projects by providing customers access to technical skills and information to overcome their social barriers.

## 8.2 Theoretical contributions

In this section, I describe the theoretical contributions of this study which relate to three areas. First, I provided a validation of the most common social barriers that hinder technology adoption in B2B markets. Second, by applying the TAM to AI technology, this investigation offers a vertical perspective on the technology providing a general structure that can be applied to multiple AI-based solutions. Lastly, this research advances an approach for third parties' organizations as the AIIC, differentiating from the traditional provider-customer relationship in B2B markets. These three areas are described in the following sections.

### *8.3.1 Social barriers to technology adoption*

Various studies place a greater emphasis on the economic and technical components of emerging technologies, overlooking the significant impact that social obstacles, such as trust, can have on customers' acceptance. Several authors started to realize this gap and analyse new technologies under a social lens. Conversely, most of the studies investigate social barriers in B2C markets leaving B2B mostly unexplored. Thus, this master thesis contributes to the literature on social barriers to technology adoption in B2B markets.

Most of the time, the resistance to new technologies derives from a lack of customers' understanding and skilled human capital (Canhoto & Clear, 2020; Brock & Wangenheim, 2019; Balta-Ozkan et al., 2013). This study considers and validates *customer awareness* and *access to technical skills* as social barriers to technology adoption. These determinants are also used as leverage points to stimulate the adoption itself. Next to this, lack of trust was one of the most recognized social barriers, so that, authors proposed adoption theories that fully rely on this determinant (Fernandes & Oliveira, 2021; Luo et al., 2019). However, this research takes a different stand, meaning that it does not recognize trust as the only determinant to technology adoption, but one of the most compelling. The barrier *lack of trust* considerably affects the impact of other obstacles (i.e., *safety, security*, and *job displacement)* as stated by Hengstler et al. (2016). Accordingly, *safety, security*, and *job displacement* become priority concerns for customers when they do not trust the solution. Therefore, this study endorses the work of Baccarella et al. (2020) which refers to safety and loss of control as technology anxiety. Moreover, it supports Złotowski et al. (2017) that proposes realistic threats (i.e., job displacement and safety) and identity threats (i.e., security) as determinants of social acceptance.

Furthermore, the results of the interviews confirmed the point of view of Dwivedi et al. (2021) and Fleming (2019) concerning job displacement. However, this study considered the experiences of both AI developers and customers' management which highlighted an interesting dissonance. Management supported the theory of Fleming (2019) recognizing a change of job demand that the market will face once AI reaches higher commercialization. Nevertheless, AI developers claimed that end-users' opposition to the technology is heavily influenced by the changes in their jobs. This latter finding is in accordance with Jarrahi (2018) and Cubric (2020). Besides, *internal support* and *social pressure* are important determinants of *intentions to use* endorsing the importance of internal and external technology acceptance. These two factors were already considered by the UTAUT, TPB, and TAM2. As a result, this study supports the importance of *facilitating conditions* (i.e., *internal support*) within the UTAUT as proposed by Venkatesh et al. (2003) as well as *subjective norms* (i.e., *social pressure*) within TPB and TAM2 (Ajzen, 1991; Venkatesh & Davis, 2000).

Lastly, this master thesis also offers an important contribution to the adoption theory adopted as foundation of the model proposed in section 6.1.1. A more detailed explanation is available in the following section.

### *8.3.2 TAM applied to AI technology*

The Technology Acceptance Model (TAM) is considered one of the most used and reliable models in the technology acceptance literature. Several authors used it to explain the acceptance of intelligent products (Sánchez-Prieto et al., 2020; Sepasgozar et al., 2019; Chen et al., 2017). However, this study contributes to the literature gap that sees TAM being mainly used for specific AI-based solutions, lacking a vertical approach to the technology. On the one hand, this investigation agrees with previous contributions describing AI as highly context specific (Dwivedi et al., 2021; Arun et al., 2020; Brock & Wangenheim, 2019). On the other hand, there are common traits that allow a vertical approach to AI as a general innovation. The social barriers to AI adoption are an example. In fact, the model presented in section 6.1.1 stands independently from the industry and specific application.

Furthermore, the model proposed does not represent only a vertical approach to AI technology, but it can be adapted to a specific industry or application. For example, *safety* within the healthcare sector had a different meaning compared to smart manufacturing. However, the negative effect on *intentions to use* and its dependence on *lack of trust* was valid for both industries. Thus, the model presents also some degrees of horizontal flexibility.

Lastly, literature analysed the acceptance among customers within a traditional perspective in which the only players in the market are providers and consumers. However, this study differs from other authors by introducing the possibility of a third party into this relationship, opening the model to organizations as accelerators, incubators, ecosystem facilitators, and more. Thus, a more detailed description is provided in the next section.

### *8.3.3 Approach of a third-party to overcome social barriers*

The launch into the market of emerging technologies is not always facilitated solely by the company responsible for its development. Third-party players, for example, start-ups accelerators or incubators, can also significantly contribute to market adoption. Depending on their vision and business model, customers usually recognized them as an objective part that can help approach the technology. Nonetheless, it is difficult for these players to accelerate adoption and overcome the social barriers with limited decision power over the technology itself.

However, the findings of this study, as well as reported by Bell et al. (2017), highlighted the lack of interest among AI developers concerning market education due to limited resources or fear of switching to the competition. At the same time, *customer awareness* and *access to technical skills* are two important leverage points to stimulate adoption. Therefore, this investigation offers an approach for third-parties players to customer education both in terms of awareness creation and access to skilled human capital.

## 8.3 Managerial recommendation for AIIC

This section compiles a list of recommendations for the AIIC to better implement the solutions developed in this study. To begin, preserving the Centre's objective position is critical to accelerate AI industrialization in the Brainport Eindhoven region. Stakeholders are presented with the AIIC as an objective link between developers and customers. This enables the Centre to facilitate a variety of activities that AI developers would be strategically unable to organize. Both the solutions developed in this study are clear examples of leveraging the AIIC's role (sections 6.2.3 and 6.3.3).

Next to this, the findings of this investigation highlight how trust towards the technology dictates the impact of other three barriers, namely *security*, *safety*, and *job displacement*. The solutions proposed help in overcoming the initial distrust of stakeholders. However, trust builds up over time. Therefore, for it to be effective, the AIIC must devise a strategy for involving potential customers in the community and maintaining the relationship active. By doing so, the Centre can easily quantify the long-term contribution of the CAP. Furthermore, because potential customers are members of the community, AI developers are more likely to share their use cases, making this step easier. Besides, if participants develop a positive image of the technology, their impact can be exponential. Social pressure was another barrier of the technology that could positively influence the intentions to use of other customers.

Moreover, the AIIC should consider a plan to involve the management of the companies that approach the Centre. Management education is crucial as also demonstrated by the lack of internal support registered among interviewees. The technology under consideration has the potential to be disruptive within a firm, not just in terms of performance but also in terms of culture change. Change management practices are key to overcome internal resistance to change. Next to this, a polarization of expectations among management has far more severe implications than the rest of the company (Barro & Davenport, 2019; Saeidi et al., 2019).

Furthermore, the Centre must update the content of the AI qualification framework and the CAP regularly. Both the technology and the market are fast-changing and so are their needs. Moreover, if no actions are taken, the market's absence of hybrid profiles would continue forcing companies to compete for limited resources. Therefore, I strongly suggest the AIIC to explore the possibility of a collaboration with Innovation Space. This offers a short and long-term impact as explained in section 6.2.3.

Lastly, the AIIC should guarantee that the use cases are transparently presented to customers. A suggestion would be emphasizing how the solution developed but without getting too technical. In fact, during this process, presenters should accentuate the value delivered over technicalities. An example would be to underline the intermediate checks between the solution and the end-users, and the feedback received in those circumstances.

### 8.4 Limitations and future research directions:

This study based its findings and implications on the European scenario. Therefore, it cannot be generalized to other no-European countries. Next to this, the research focuses specifically on two sectors, namely healthcare and smart manufacturing. Thus, the results and recommendations of this study might not apply, or only partially, to other sectors (e.g., finance, education, etc.). This is because AI is a highly context-specific technology in which project specifications could significantly differ from one another. The complexity of an AI-based solution is determined not only by the industry, but also by the individual application inside a company. However, as mentioned above, the vertical approach of this study towards the technology allows the identification of a general structure that can be later adapted to specific contextual circumstances. Future research could consolidate the findings of this study and investigate which adaptations are required in different contexts. Another possibility is to compare the findings of this research, which focused on a B2B context, to those of a B2C study. It might be interesting for companies that operate in both markets with distinct products. By identifying the commonalities and differences within the two contexts, companies could better adapt their approach and promoting emerging technologies while overcoming social barriers.

Furthermore, this study presents the typical limitations of qualitative analysis. Thus, the study is still based to a certain degree of subjectivity. Next to this, in this research, each interviewee is representative of the wishes of the whole company. However, as shown in section 5.1.6 (the cognitive dissonance of job displacement), the wishes of the whole firm are difficult to represent. Thus, the use of the proposed model within a specific organization and its several departments can be a future research approach.

The distinction between skills and competencies was a source of confusion among interviewees, who found it easier to identify job profiles. Therefore, while qualifications are in response to a specific job description and thus specific skills are required, the research issue is partially addressed. Future research should go deeper into this topic by involving respondents who are closer to the recruitment process or who work in human resources. Besides, the twelve qualifications presented are the direct results of the interviews conducted. However, further research could validate or integrate other qualifications. Moreover, due to the nature of the internalisation step the AIIC cannot control its outcome. For this reason, the design requirements of the fourth step of the CAP are in minority compared to the previous three stages. Therefore, the success of the Program also depends on the follow up actions that the Centre desires to take.

The results of the interview also highlighted three topics that future investigations could consider. First, the absence of a hybrid profile in the market. Potential research questions could address how to introduce such profile within the traditional curricula, which would be the role of the educational ecosystem and the best way to act. Besides, it is not known yet how the curricula should be composed. The only apparent conclusion is that the student should have knowledge, skills, and responsibilities in both industry and technology. However, there are no indications of the potential skills required for this profile. Therefore, I suggest tackling this topic through an explorative approach based on qualitative analysis. In this way, new insights collected will define this profile more precisely and allow the identification of key factors and relationships. Furthermore, it is critical, to begin with, a qualitative analysis because respondents may have a different interpretation of the profile, potentially leading to contradicting findings.

Second, participants mentioned the fragmentation of the European scenario on multiple occasions. On the one hand, certain EU countries are more stringent than others in certain security regulations. On the other hand, five regions are far ahead in terms of AI breakthroughs. This raises a common question that has no answer yet: "is Europe supporting or hindering AI development and adoption?". The answer to this research question is not easy to tackle because of the number of different stakeholders involved. Therefore, I suggest selecting a target group (i.e., demand-side, supply-side; public demand, private demand) and consider direct and indirect types of support (Edler, 2013). For example, understanding which demand-side policy instruments are significant in the smart manufacturing industry and how the EU is approaching them. In this case, depending on the availability of data, a quantitative analysis is preferred.

Third, governments are expected to manage AI's transition and mitigate its impact by retraining people in the skills required for new occupations. This might be an interesting field of research, with questions ranging from what policies and instruments are needed to assist such a transition to the new skills required. As well as in the first case, I suggest an exploratory approach to this research topic to better define the challenges that such transition would lead. Next to this, it is important to tailor this investigation to specific industries to better identify the new skills required.

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# Appendix A: Secondary sources of this study

1. **European Commission report (2020)**
    - ***Title***: A European approach to Artificial Intelligence
    - ***Use within the study:*** Analyze the industrial context of AI
    - Retrieved March 01, 2021 from: https://ec.europa.eu/digital-single-market/en/artificial-intelligence
2. **European Commission report on AI (2020)**
    - ***Title***: Artificial Intelligence (AI)
    - ***Use within the study:*** Analyze the industrial context of AI
    - Retrieved March 19, 2021, from: https://ec.europa.eu/info/research-and-innovation/research-area/industrial-research-and-innovation/key-enabling-technologies/artificial-intelligence-ai_en
3. **European Commision workshop report (2018)**
    - ***Title:*** *The European AI Landscape*
    - ***Use within the study:*** Analyze the industrial context of AI
    - Retrieved March 19, 2021, from: https://knowledge4policy.ec.europa.eu/publication/european-ai-landscape_en
4. **Europass European Union standard (2017)**
    - ***Title:*** Description of the eight EQF levels
    - ***Use within the study:*** European standard for the AI qualification framework to identify the level of expertise required in each qualification.
    - Retrieved July 07, 2021 from: https://europa.eu/europass/it/description-eight-eqf-levels
5. **High Tech Campus internal investigation (2020)**
    - ***Title:*** High Tech Campus Eindhoven Towards 2030.
    - ***Use within the study:*** Analyze company context and identify problem statements and research question.
    - ***Retrieved:*** internal HTC documentation
6. **AIIC internal documentations for the kick-off event (2021)**
    - ***Use within the study:*** Analyze current action and vision of the AIIC, understand its business model and the fit with the solutions designed
    - ***Retrieved:*** internal AIIC documentation
7. **AIIC internal documentations for education (2021)**
    - ***Use within the study:*** Analyze current action and vision of the AIIC, understand its business model and the fit with the solutions designed
    - ***Retrieved:*** internal AIIC documentation

# Appendix B: Interview Protocol

## INTERVIEWS TO AI DEVELOPERS

**GENERAL GOALS:**

1. Validation of social barriers
2. Guideline of technical skills/expertise needed for AI adoption

**DEMOGRAPHIC DATA:**

**Industry:**

**Role(s):**

**Country:**

**Date:** XX/XX/XXXX

*10/15 minutes*

*Brief presentation of myself and explanation of my research, its goals and AIIC. I will then ask to the participant if it is possible to record the interview and that it will be transcribed, anonymized and if possible, revise it by the participant him/herself.*

*Brief presentation of the participant.*

- Role & Responsibilities within the company.
- Pitch of the AI solution(s).

**INTERVIEW QUESTION:**

*30 minutes*

- **Validation of social barriers:**

1. What did you experience while talking with customers about your solution(s) as AI-based technology?
2. If there would be no economic or technical boundaries, which do think would be the reasons for your customers to not adopt AI?
3. Could you tell me some anecdotes in which customers really needed the technology but decided to not adopt? Why do you think that happened?

*15 minutes*

- **Exploration of technical skills for AI adoption:**

4. Which qualifications do you think might help the customers in adopting the technology?
5. How could the customer access to them?

- **Follow up on the social barriers validation**

6. To what extent do you consider customers being informed about AI?
7. To what extent customers have access to the qualifications necessary to implement and use AI?
8. To what extent do you think customers trust the technology?
9. How are safety or security issues influencing customers' decision to adopt?
10. To what extent do you consider job displacement as an obstacle to AI adoption?

# INTERVIEWS TO POTENTIAL CUSTOMERS (COMPANIES)

**GENERAL GOALS:**

1. Understand where the customers lack of knowledge in order to prioritize the contents of the customer awareness program (i.e. definition, benefits, limitations or potential use)
2. Understand if the customer recognizes the necessity of technical skills in order to adopt the technology. If yes, which ones are common.

**DEMOGRAPHIC DATA:**

**Industry:**

**Role(s):**

**Country:**

**Date:** XX/XX/XXXX

*10/15 minutes*

*Brief presentation of myself, AIIC and introduction of the study without influencing the customers on definitions or specific topics. I will then ask to the participant if it is possible to record the interview and that it will be transcribed, anonymized and if possible, revise it by the participant him/herself.*

*Brief presentation of the participant.*

- Role & Responsibilities within the company.
- Educational/Technical background.

**INTERVIEW QUESTION:**

<u>*50 minutes*</u>

- **AI technology & Social barriers**

1. How would you define Artificial Intelligence?

2. Which is your overall opinion about this technology?

3. Why would you (not) consider applying AI within your company?

    a. To what extent do you think you know this technology?
    b. To what extent safety and security issues keep you from adopting AI?
    c. To what extent do you think AI 'job displacement' might be a problem within your company?

- **General Benefits & Limitations**

4. In your opinion, which are the common benefits of adopting such technology? Could you list some advantages?

5. Could you think of any technical limitations/disadvantages that the technology might bring in general?

- **Context-specific: potential application in the industry**

6. Could you name some potential applications of AI within your industry?

7. Pick one application among those you just mentioned that you think you know best. Which are the benefits in your daily work performances or the one of your colleagues?

8. In this regard, can you also think of any technical limitation within your/your colleagues daily work performances?

- **Context -specific: Technical skills**

9. Which skills do you think would be useful to successfully adopt the application?

## INTERVIEWS TO FOUNDERS AIIC

**GENERAL GOALS:**

1. Understand which are the requirements that the Customer Awareness Program (CAP) must respect to be successfully implemented within AIIC practices.

**Date:** XX/XX/XXXX

**INTERVIEW QUESTION:**

_30 minutes_

1. How do you think the Customer Awareness Program should look like?

2. Which top requirements should be integrated within the Program?

3. Which are the expected benefits from this Program?

4. How often would you like to run the Program? And how long do you think the session(s) should be?

5. Who do you think should join the Program?

6. There is a clear need in the market for showcasing, who do you think should organize it within the Program?

7. Who do you think should organize the practical content within the Program?

## Appendix C: Characteristics of the interviewees

| Interviewees | Role within this study | Size of the company | Country | Industry | Job function |
|---|---|---|---|---|---|
| *Interviewee 1* | AI developer | Large company | Germany | Smart manufacturing | Vice President AI & Expert for the EU commission |
| *Interviewee 2* | AI developer | Large company | Netherlands | Healthcare | Technical and Business Development Lead |
| *Interviewee 3* | AI developer | Start-ups | Denmark | Healthcare | Chief of Operations |
| *Interviewee 4* | AI developer | Large company | Netherlands | Healthcare | Vice President AI |
| *Interviewee 5* | AI developer | SME | Netherlands | Smart manufacturing | CEO |
| *Interviewee 6* | AI developer | Large company | Netherlands | Smart manufacturing | Business Developer in autonomous driving |
| *Interviewee 7* | AI developer | Large company | Netherlands | Smart manufacturing | Team Lead System Innovations |
| *Interviewee 8* | AI developer | Start-ups | Lithuania | Healthcare | Co-Founder & CFO |
| *Interviewee 9* | Potential customer | SME | Netherlands | Smart manufacturing | CEO |
| *Interviewee 10* | Potential customer | SME | Netherlands | Smart manufacturing | Senior Director Mixed-Signal design |
| *Interviewee 11* | Potential customer | Start-up | Netherlands | Smart manufacturing | CEO |
| *Interviewee 12* | Potential customer | SME | Netherlands | Healthcare | CEO |
| *Interviewee 13* | Potential customer | SME | Netherlands | Healthcare | Founder |
| *Interviewee 14* | Potential customer | Large company | Hungary | Smart manufacturing | Mobility development officer |
| *Interviewee 15* | Potential customer | Large company | Austria | Smart manufacturing | Program Manager |
| *Interviewee 16* | Potential customer | SME | Netherlands | Healthcare | Research Principal |
| *Interviewee 17* | Potential customer | Large company | Netherlands | Healthcare | CIO |
| *Interviewee 18* | Potential customer | Start-up | Germany | Healthcare | Founder |

| | | | | | |
|---|---|---|---|---|---|
| *Interviewee 19* | Founder AIIC | Start-up | Netherlands | Healthcare, smart manufacturing, smart energy. | Founder |
| *Interviewee 20* | Founder AIIC | Start-up | Netherlands | Healthcare, smart manufacturing, smart energy. | Founder |

*Table 6: In total this study includes the interviews to twenty people which belongs to different company's size, country, industries and functions. However, there are three target groups, namely (i) AI developers, (ii) potential customers and (iii) AIIC founders.*

| **Interviewees' characteristics** | |
|---|---|
| Size of the company | ***Corporate***: 45% of the total interviewees<br>***SMEs***: 33% of the total interviewees<br>***Start-ups***: 22% of the total interviewees |
| Country | ***The Netherlands***: 67% of the total interviewees<br>***Other EU countries:*** 33% of the total interviewees |
| Industry (semiconductors, nanotech, automotive, transportation, smart industry, medical services, manufacture of medical equipment/devices) | ***Smart Manufacturing:*** 50% of the total interviewees<br>***Healthcare:*** 50% of the total interviewees |
| Job function | ***Management:*** 61% of the total interviewees<br>***Other functions:*** 39% of the total interviewees |

*Table 7: The overview of the interviewees' characteristics is divided into (i) size of the company, (ii) country, (iii) industry and (iv) job function.*

## Appendix D: Codebook of the interviews

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Social Barriers* | *Access to technical skills* | *Tech-adverse end user* | Individual end user which is not comfortable is using new technologies. |
| | | *Tech-adverse company* | Company which is not comfortable is adopting new technologies. |
| | | *Lack of data science expertise* | Absence of skills and knowledge regarding data science discipline. |
| | | *Lack of cloud knowledge* | Absence of skills and knowledge regarding cloud computing technology. |
| | | *State-of-the-art internal data knowledge* | Absence of knowledge from the customers' side regarding the current picture of their data. |
| | *Customer Awareness* | *Lack of basic knowledge* | Inadequate knowledge regarding some fundamental aspects of the technology as benefits and limitations of the technology (Rogers, 1995). |
| | | *Lack of risk management practices* | Absence of practices that helps in overcoming the risk of investments in new technologies and dealing with the uncertainty that comes with it (Canhoto & Clear, 2020). |
| | | *Need of showcasing* | Market necessity of seeing the technology applied in their sector, namely use cases. |
| | | *Lack of application knowledge* | Absence of knowledge regarding potential application of the technology and the steps necessary to take in order to apply it. |
| | *Lack of trust* | *Lack of willingness* | Lack of interest in trying out the technology or taking any risk in that direction. |
| | | *Fear of worse situation* | Reluctance of using the technology because customers expect negative consequences. |
| | | *Dealing with uncertainty* | Reluctance of customer to deal with the ambiguity that a new technology might bring. |
| | | *Delegating control over the system* | Reluctance of the customers to authorize the system on performing tasks on their behalf. |
| | | *Ethical principles* | It is related to the responsibility and ownership of the decisions made by AI on topics as: "*processes relating to AI and human behaviour, compatibility of machine versus human value judgement, moral dilemmas and AI discrimination"*. (Dwivedi et al., 2021, p.6) |
| | | *Discomfort talking about AI* | Certain level of apprehension noticed among customers when referring to AI solutions. |
| | | *Misunderstanding of AI* | Customers assumptions on the technology are based on media's influence which does not match the reality. |
| | | *Lack of experience* | Insufficient customers' practice with the technology. |

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Social Barriers* | *Safety* | *Heterogeneity of data* | Customers are afraid that the variety of the data used to train the algorithm is not representative of the population. |
| | | *Reliability of the system* | The algorithm or the solution is perceived as not trustworthy by the customers. |
| | | *Ownership of decisions* | The customers want to keep the responsibility that derive from decision-making processes. |
| | | *Physical threat* | The technology is perceived as dangerous for the physical wellbeing of customers. |
| | | *Legal implications* | The misuse of the technology has some repercussion for the law. |
| | | *Lack of outcome transparency* | Absence of understanding how the algorithm came to a specific outcome or if the outcome is an outlier. |
| | *Security* | *Workers surveillance* | Stakeholders are afraid that employers monitor their employees in a way that violates their privacy. |
| | | *Use of data for second purposes* | Customers are afraid that the data collected to train and execute the algorithm will be used for different purposes than the ones declared. |
| | | *Data privacy* | Customers are afraid that the technology or the data collected in order to execute the algorithm, violates their privacy. |
| | | *Cyberattacks* | Customers are afraid that by using AI their cyber-vulnerability increases and put them in unpleasant situations. |
| | | *Severe country policies* | The European scenario is quite fragmented regarding security policies and some countries are stricter than others. |
| | | *Compensation for data exchange* | Some customers believe that in exchange of their data, AI developers must pay a indemnity. |
| | *Job displacement* | *New skills required* | Customers recognize that new competences are required in order to fully benefit from the technology. |
| | | *Change in performance* | Customers are afraid that the KPIs of their job will change. |
| | | *Fear of losing the job* | Customers believes that the technology will take over their current position. |
| | | *Shift on job demand* | Customers recognise that some jobs will become obsolete but new positions will be created thanks to the technology. |
| | *Internal support* | *Lack of change management* | Absence of resources and practices that can address the change that a new technology brings into the company. |

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Social Barriers* | *Internal support* | *Lack of processes* | Absence of internal processes that can facilitate the introduction of a new technology within the firm. |
| | | *Lack of management support* | Absence of any kind of support from the management of the company. |
| | | *Lack of internal infrastructure* | Inadequate technical infrastructure that can help integrating the technology within the company. |
| | *Social pressure* | *Societal opinions* | Overall society's assessment of the technology. |
| | | *Internal stakeholders' perspective* | The overall feedback that internal stakeholders have about the technology. |
| | | *External stakeholders' perspective* | The overall feedback that external stakeholders have about the technology. |
| | | *Strategy of the competition* | Approach that the competition is taking in regards of the technology adoption. |
| | | *Government pressure* | Array of regulations that governments set to steer the development of the technology. |
| *Registered difficulties* | *Information from the customer* | *Hazy understanding of claims* | The explanations of the customers were not clear enough to understand the reason of no adoption. |
| | | *Unfounded claims* | The explanation of the customer to not adopt were based on groundless believes. |
| | *Communication towards the customer* | *Importance of value delivered over technology* | The AI developers emphasized the importance of how the customers would benefit from the AI-based solution instead of explaining the technicalities of the technology. |
| | | *Customer involvement* | AI developers engaged with the customers during the development of the solution through intermediate checks between the start and the end of the product development process. |
| | | *Expectations management* | AI developers found difficult to communicate and understand the expectations of the customers and consequently deliver upon those promises. |
| | | *Management as first target* | Management must be involved first to successfully adopt the technology. |
| | | *Scientific validation* | Customers claimed for scientific confirmation of the technology's performance (e.g. accuracy) which in some cases AI developers needed to provide to sell the solution. |
| | *Data minimization* | *Identify minimal data needs* | Difficulties in expressing the minimal data necessary in order to train the algorithm and guarantee trustworthiness. |
| | *Legal framework* | *Fragmented EU regulation* | European countries do not present a uniform approach to regulate AI's impact. |
| | | *Differences between EU and international scenario* | European countries present a different approach to regulate AI's impact compared to the rest of the world. |

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Technical skills needed* | *Technology-oriented domain* | *Data scientist* | Multidisciplinary profile that combines computer science, statistics and mathematics and present specific skills identified by Costa & Santos (2017). |
| | *Data-oriented domain* | *Data quality manager* | Responsible for the identification, communication and assessment of data quality standards with respect to accuracy, timeliness, completeness and credibility (Khatri & Brown, 2010). |
| | | *Up-to-date ICT employees* | Employees working in the ICT department are aware of the last technology trends in that field and consequently how to use modern IT infrastructure. |
| | | *Data steward* | Data architects are responsible for "*establishing the semantics or 'content' of data so that it is interpretable by the users"* (Khatri & Brown, 2010). |
| | | *Data custodian* | "*Asset data is managed by the data custodian on behalf of Company A. (…) They are also responsible for endorsing data management plan, endorsing data cleansing plan, ensuring data is fit for purpose*." (Cheong & Chang, 2007, p. 1005). |
| | | *Business translator* | This profile should help AI developers in translating a business problem into requirements to be included within the AI project. |
| | | *Analytic translator* | This profile should help AI developers in translating business requirements into analytic processes. |
| | | *Data architect* | Data architects are responsible for "*establishing the semantics or 'content' of data so that it is interpretable by the users"* (Khatri & Brown, 2010). |
| | *Industry-oriented domain* | *Industry expert* | Characteristic know-how from individuals which determine specific industry knowledge. |
| | | *Ethical expertise* | Know-how concerning the ethical aspects that an X solution might threat, and which is the best way to act. |
| | | *Legal expertise* | Know-how concerning the legal aspects that an X solution might threat and how to overcome such risks. |
| | | *Hybrid profile* | Individual that has both industry experience and technological knowledge. |
| AI benefits | *Operational benefits* | *Dealing with complexity* | The technology allows the customer to handle the complexity that certain tasks might have by simplifying their management. |
| | | *Higher efficiency* | The technology allows the customer to execute tasks both faster and with higher performances. |
| | | *Process automation* | The technology allows the company to automate certain tasks that before were performed by employees. |
| | | *Higher cognitive tasks* | Through the automation of certain tasks, professionals can focus their effort in higher cognitive tasks. |

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Benefits of AI* | *Data analysis* | *New insights from data* | The technology allows the customer to retrieve information from data not possible otherwise. |
| | | *Outcome prediction* | The technology allows the customer to predict future trends in the data. |
| | *Long-term benefits* | *Competitive advantage* | The technology allows the customer to build and ensure competitive advantage compared to other market players. |
| | | *Improve quality of products* | Through the operational benefits, the technology can increase the quality of the products in which it is applied. |
| | | *Improve quality of life* | The technology will impact not only the company but also the society delivering higher work/life standards. |
| | | *Improve safety of products* | Through the operational benefits, the technology can increase the safety of the products in which it is applied. |
| *Limitation of AI* | *Transparency* | *Biased data* | The technology relies on data, so when data are biased towards a certain outcome, also the technology will represent that trend. |
| | | *Understanding the outcome* | Recognising when the outcome is an outlier and be able to manage that situation. |
| | | *Full reliance on data* | The outcome of technology fully depends on the training data that has been used initially and the dataset in which it is working. |
| | *Responsibility* | *Ownership of the failure* | Once there is a mistake, it is not clear who should take responsibility for that mistake. |
| | | *Technical dependency* | AI can perform different tasks, but it is important that employees know how to perform those activities in case of a discontinuity of service and do not rely completely on the machine. |
| | *AI implementation* | *Specificity of the problem definition* | Defining the right business problem result in determining the purpose of the technology. However, the degree of details and the boundaries are difficult to establish. |
| | | *Malignus purpose of the algorithm* | The technology can be developed to perform illegal activities. |
| | | *Availability of data* | AI technology needs considerable amount of data with respect to data quality standard. For some companies this might be not possible. |
| | | *Discontinuity of the service* | Companies must develop an alternative plan in case the technology stops working. |
| *Content CAP* | *Data knowledge* | *Update IT management* | Knowledge related modern IT infrastructure needed in order to adopt AI (i.e. cloud technology) |

| Aggregate dimension | Second order codes | First order codes | Definition |
|---|---|---|---|
| *Content CAP* | *Data knowledge* | *Difference between data quality* | Basic knowledge regarding the difference between the different stages of data quality with respect to accuracy, timeliness, completeness and credibility. |
| | | *State-of-the-art of internal data* | Understanding the data asset of the company in terms of data kind (structured, unstructured), formats, sources etc. |
| | *Technology assessment* | *AI as support-decision tool* | The technology is a tool that allows professionals to make better decisions based on data. |
| | | *Influence on the professional assessment* | Understanding the impact that the technology will have on the KPIs the professionals must deliver in order to successfully accomplish their tasks. |
| | | *Benefits of adopting AI* | Understanding the basic benefits that the technology delivers within the company in the short and long term. |
| | | *Limitations of AI* | Understanding the basic limitations that characterized the technology and might influence its implementation and performances. |
| | | *Definition of AI* | Basic understanding of what AI actually entails. |
| | | *Industry application* | Understanding of the potential application of the technology within the market through showcasing. |
| | | *Cost/benefit ratio* | Understanding which is the average cost of implementing and AI solution compared to the benefits it will deliver. |
| | *Technology development* | *Parameter setting of the technology* | Understanding the difficulties of setting the right parameter to train the algorithm within the purpose assigned. |
| | | *Experimental character of AI* | Understanding that the technology is highly context specific and that its development needs reiteration and intermediate checks. |

*Table 8: This is codebook used to codify the interviews of this study for both target groups, namely (i) AI developers and (ii) potential customers.*

## Appendix E: Coding schemes of the interviews

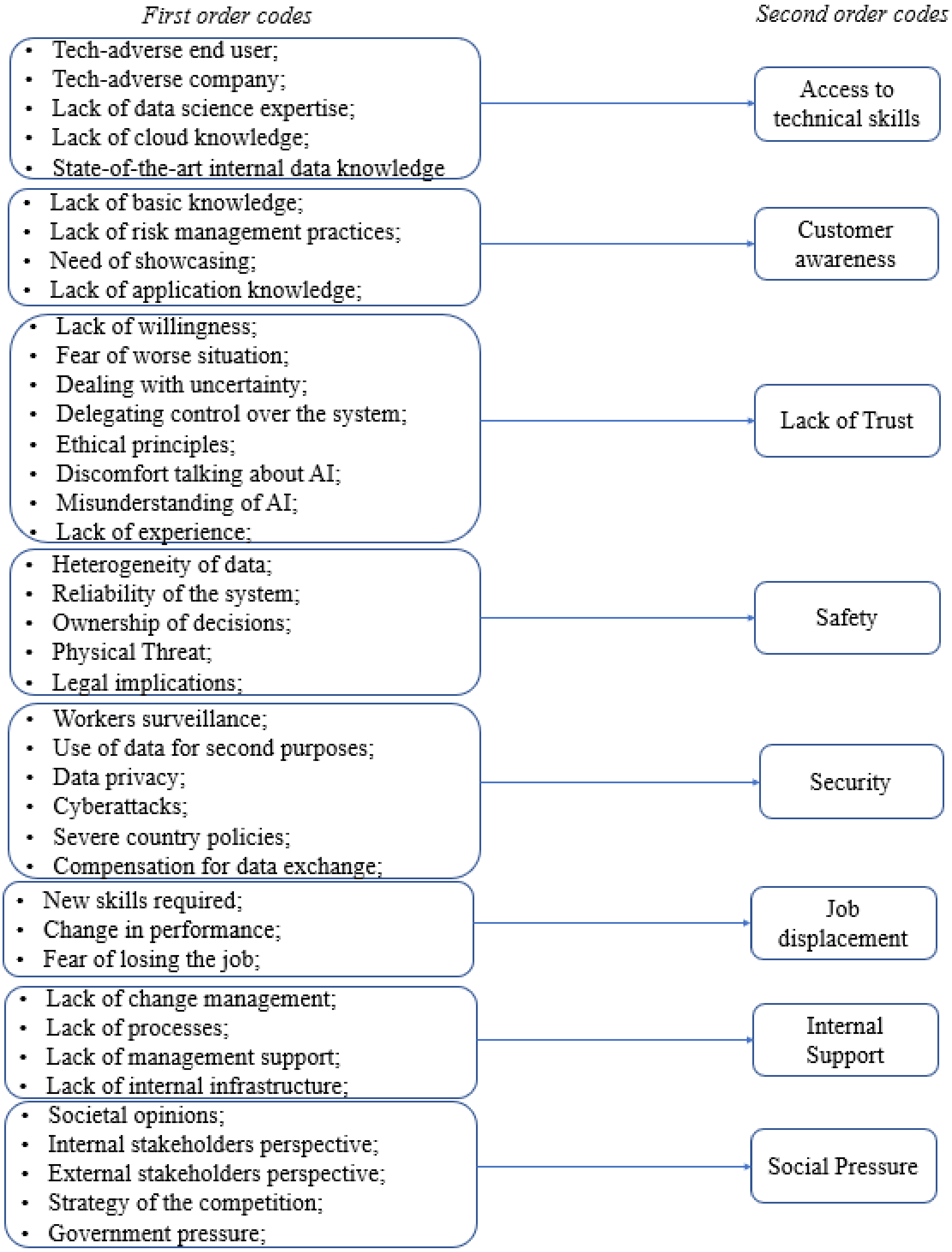


*Figure 19: The coding scheme here presented is the result of the interviews conducted to AI developers which was used to validate the social barriers previously identified in the literature and answer to one of the sub-questions of this study.*

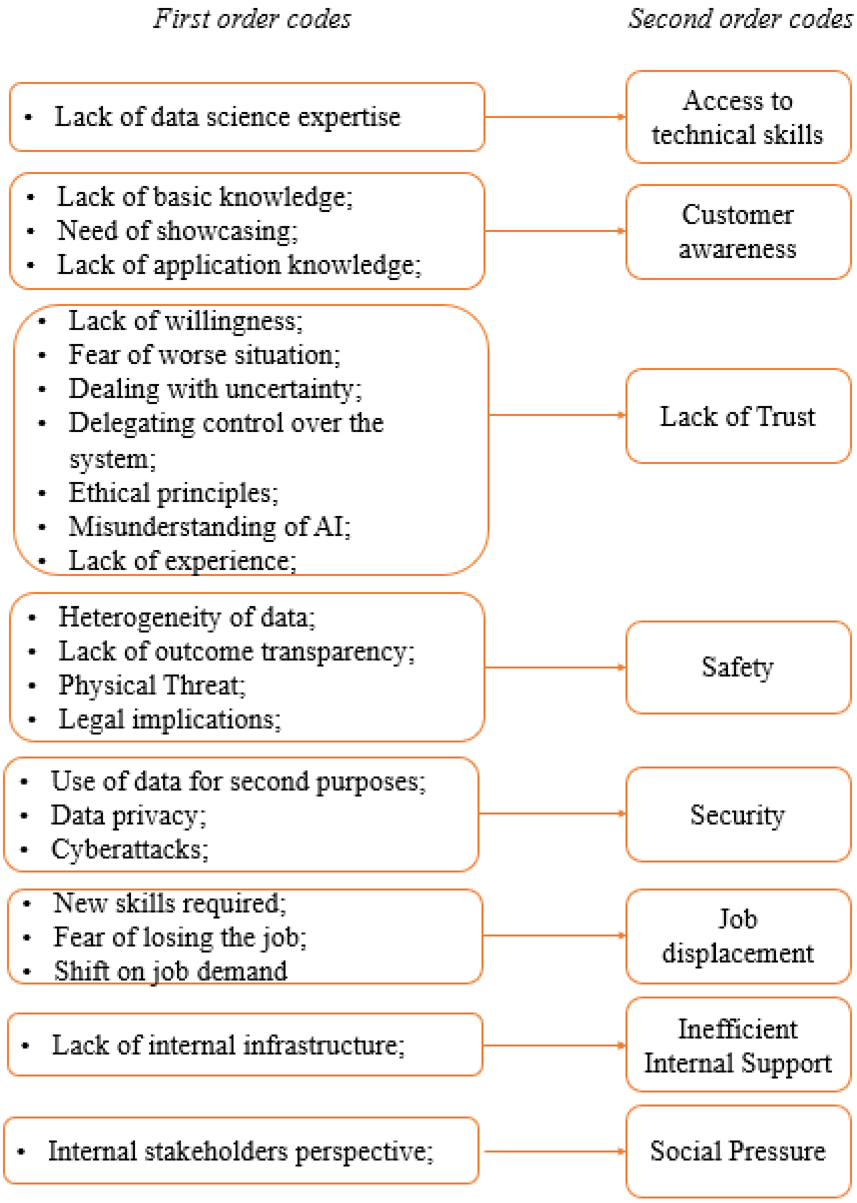


*Figure 20: The coding scheme here presented is the result of the interviews conducted to potential customers which was used to validate the social barriers previously identified in the literature and answer to one of the sub-questions of this study.*

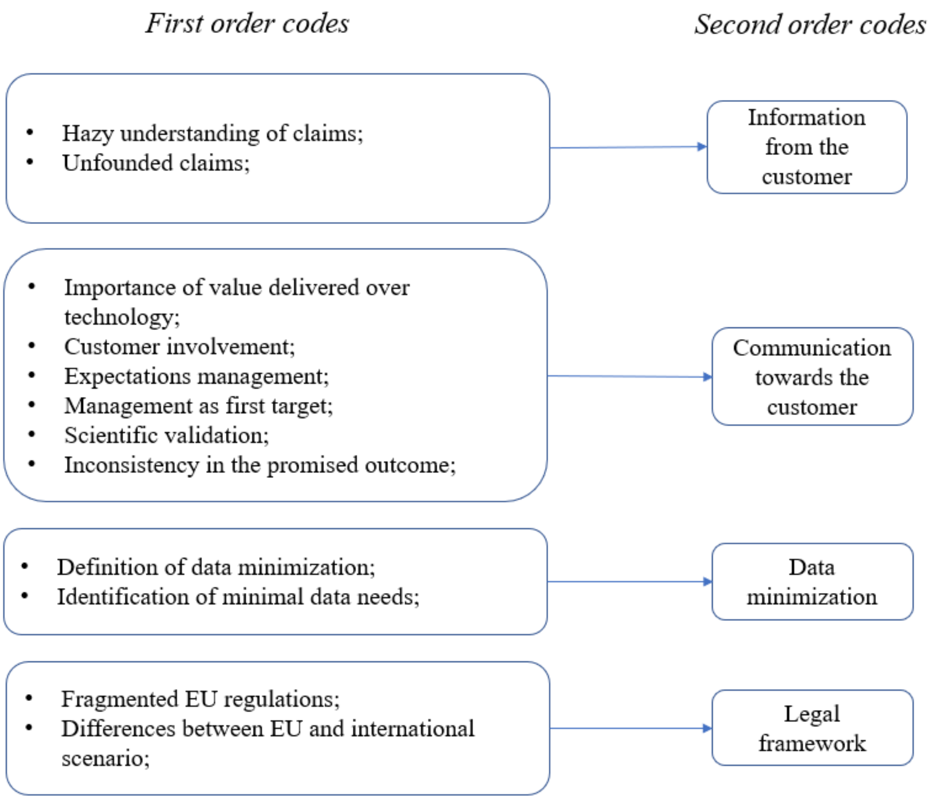


*Figure 21: AI developers encountered different difficulties while talking with customers about their AI-based solution. These adversities were caused by (i) unclear information from the customer, (ii) the communication towards the customer, (iii) data minimization and (iv) the legal framework.*

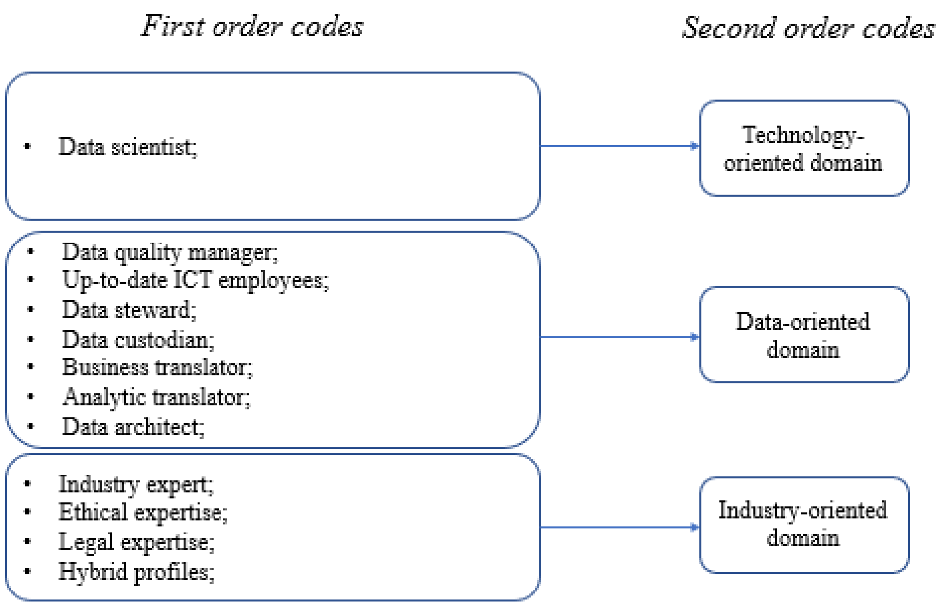


*Figure 22: AI developers identified three domains which customers should have access to certain qualifications to successfully implement AI, namely (i) technology-oriented domain, (ii) data-oriented domain and (iii) industry-oriented domain.*

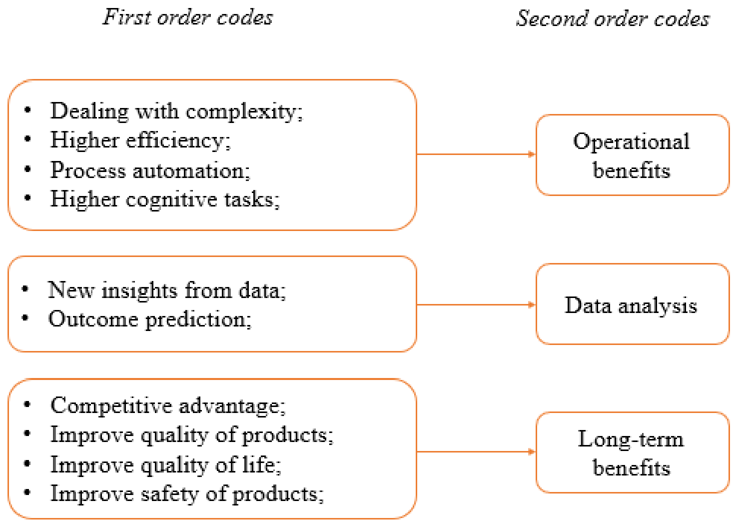


*Figure 23: Potential customers identified three categories of benefits that AI would bring in case of adoption, namely (i) Operational benefits, (ii) data analysis and (iii) long-term benefits.*

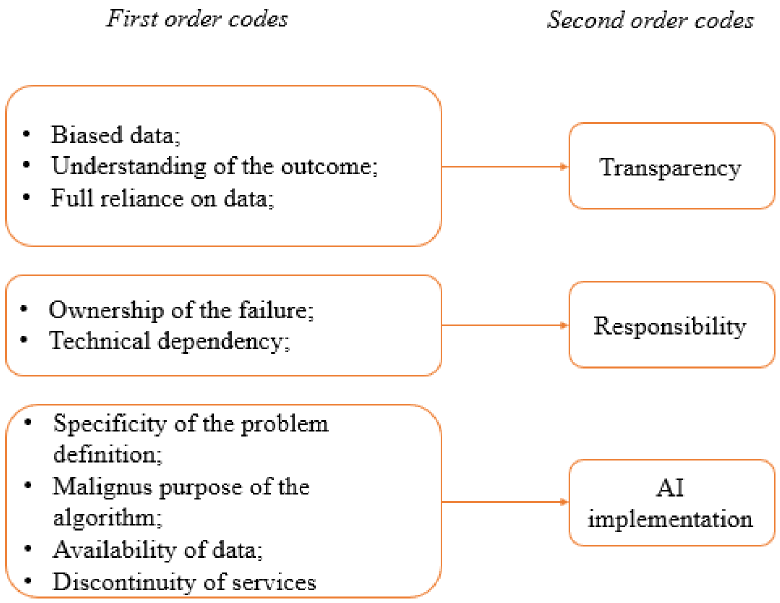


*Figure 24:Potential customers indirectly identified three categories of limitations that characterized AI, namely (i) transparency, (ii) responsibility and (iii) AI implementation.*

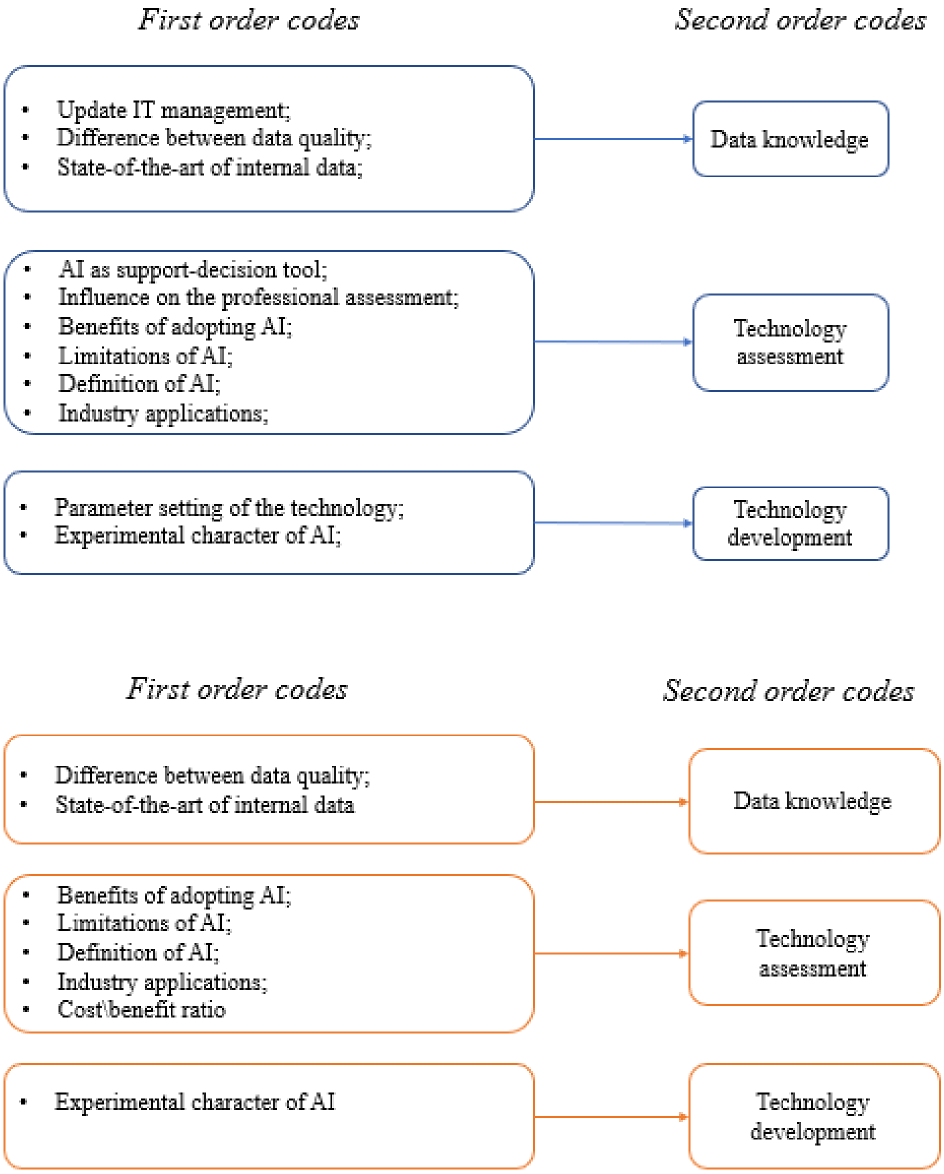


*Figure 25: Both the AI developers (i.e. blue) and potential customers (i.e. orange) identified three kinds of content the Customer Awareness Program should include based on the overall level of awareness of the market.*

## Appendix F: Definition of AI provided by the interviewees

| Interviewees | AI definition | Characteristics of AI |
|---|---|---|
| Interviewee 9 | *"I think is a <u>self-learning software system</u> which allows you to go to <u>big data</u> in the more efficient way <u>that the human brain can do</u>."* | ✓ Self-learning system;<br>✓ Linked to big data;<br>✓ Human-like tasks;<br>✗ Flexible adaptation;<br>✗ Training comes from data; |
| Interviewee 10 | *"AI to me is an algorithm or software program that has the capability of <u>learning itself.</u> (…). To me AI means it has the <u>ability to adapt</u> to what happens and improve over time."* | ✓ Self-learning system;<br>✓ Human-like tasks;<br>✓ Flexible adaptation;<br>✗ Training comes from data;<br>✗ Linked to big data; |
| Interviewee 11 | *"I would say a system-software that goes further than a simple algorithm. It's not simply math doing something repetitive over and over again, but it's growing on its own once it's generated. At some level it <u>becomes better than the instant that you use it</u>."* | ✓ Flexible adaptation;<br>✗ Self-learning system;<br>✗ Linked to big data;<br>✗ Training comes from data;<br>✗ Human-like tasks; |
| Interviewee 12 | *"For me it's all new as well, AI is about collecting data and then <u>from data you can make different analysis</u>. You can also predict which is the <u>behavior in the future</u> or what kind of patient will need this and which something else."* | ✓ Linked to big data;<br>✓ Flexible adaptation;<br>✗ Self-learning system;<br>✗ Human-like tasks;<br>✗ Training comes from data; |
| Interviewee 13 | *"It's an advanced way of trying to get <u>knowledge out of data</u>. (…). Without putting a model in front, it allows you to get a lot of wisdom out of the data without necessary knowing a lot about the data before."* | ✓ Linked to big data;<br>✗ Self-learning system;<br>✗ Human-like tasks;<br>✗ Training comes from data;<br>✗ Flexible adaptation; |

| Interviewees | AI definition | Characteristics of AI |
|---|---|---|
| Interviewee 14 | *"I think AI it's a method that you can find the optimal solution and the most efficient solution to your problem. It will be always faster than if you do it with human work."* | ✓ Human-like tasks;<br>× Linked to big data;<br>× Self-learning system;<br>× Training comes from data;<br>× Flexible adaptation; |
| Interviewee 15 | *"For me AI are algorithms that replace decisions that we make by using our brains. This is done by an algorithm that has the capability to learn and improve itself. That's for me AI."* | ✓ Self-learning system;<br>✓ Human-like tasks;<br>× Linked to big data;<br>× Training comes from data;<br>× Flexible adaptation; |
| Interviewee 16 | *"In a technical way, I know that there is a narrow variant and a broader one. (...). They bring in solutions without knowing how the machine did that. This machine learning, well machine learning, is something different from AI. At least a computer is learning by itself and by competing with some other computers and making each other more intelligent."* | ✓ Self-learning system;<br>× Linked to big data;<br>× Training comes from data;<br>× Flexible adaptation;<br>× Human-like tasks; |
| Interviewee 17 | *"(...) it is about helping humans with a constant capability of thinking based on data. I think that computers can do this much better than humans. If you have good data, also the way humans think is based on data, so the structure of the data defines how we think."* | ✓ Human-like tasks;<br>✓ Linked to big data;<br>× Training comes from data;<br>× Flexible adaptation;<br>× Self-learning system; |
| Interviewee 18 | *"I would say to make our business scale easier and to make not needed to have instead of a whole team of people, to make it more efficient. To reach the outcome that without AI would take much longer."* | ✓ Human-like tasks;<br>× Training comes from data;<br>× Flexible adaptation;<br>× Self-learning system;<br>× Linked to big data; |

*Table 9: The table above offers an overview of the answers of potential customers to the question "How would you define artificial intelligence?" listing the features of the technology that are recognized and not.*

# Appendix G: European Qualification Framework (EQF)

| | Knowledge | Skills | Responsibility and autonomy |
|---|---|---|---|
| | *Knowledge is described as theoretical and/or factual.* | *Skills are described as cognitive (involving the use of logical, intuitive and creative thinking) and practical (involving manual dexterity and the use of methods, materials, tools and instruments)* | *Responsibility and autonomy is described as the ability of the learner to apply knowledge and skills autonomously and with responsibility.* |
| Level 1 | Basic general knowledge. | Basic skills required to carry out simple tasks. | Work or study under direct supervision in a structured context. |
| Level 2 | Basic factual knowledge of a field of work or study. | Basic cognitive and practical skills required to use relevant information in order to carry out tasks and to solve routine problems using simple rules and tools. | Work or study under supervision with some autonomy. |
| Level 3 | Knowledge of facts, principles, processes and general concepts, in a field of work or study. | A range of cognitive and practical skills required to accomplish tasks and solve problems by selecting and applying basic methods, tools, materials and information. | Take responsibility for completion of tasks in work or study; adapt own behaviour to circumstances in solving problems. |
| Level 4 | Factual and theoretical knowledge in broad contexts within a field of work or study. | A range of cognitive and practical skills required to generate solutions to specific problems in a field of work or study. | Exercise self-management within the guidelines of work or study contexts that are usually predictable, but are subject to change; supervise the routine work of others, taking some responsibility for the evaluation and improvement of work or study activities. |
| Level 5 | Comprehensive, specialised, factual and theoretical knowledge within a field of work or study and an awareness of the boundaries of that knowledge. | A comprehensive range of cognitive and practical skills required to develop creative solutions to abstract problems. | Exercise management and supervision in contexts of work or study activities where there is unpredictable change; review and develop performance of self and others. |
| Level 6 | Advanced knowledge of a field of work or study, involving a critical understanding of theories and principles. | A comprehensive range of cognitive and practical skills required to develop creative solutions to abstract problems. | Manage complex technical or professional activities or projects, taking responsibility for decision-making in unpredictable work or study contexts; take responsibility for managing professional development of individuals and groups. |
| Level 7 | Highly specialised knowledge, some of which is at the forefront of knowledge in a field of work or study, as the basis for original thinking and/or research.<br>Critical awareness of knowledge issues in a field and at the interface between different fields. | Specialised problem-solving skills required in research and/or innovation in order to develop new knowledge and procedures and to integrate knowledge from different fields. | Manage and transform work or study contexts that are complex, unpredictable and require new strategic approaches; take responsibility for contributing to professional knowledge and practice and/or for reviewing the strategic performance of teams. |
| Level 8 | Knowledge at the most advanced frontier of a field of work or study and at the interface between fields. | The most advanced and specialised skills and techniques, including synthesis and evaluation, required to solve critical problems in research and/or innovation and to extend and redefine existing knowledge or professional practice. | Demonstrate substantial authority, innovation, autonomy, scholarly and professional integrity and sustained commitment to the development of new ideas or processes at the forefront of work or study contexts including research. |

*Figure 26: The European Qualification Framework consists of eight level of proficiency which extend from the basic knowledge, skills and autonomy (i.e. level 1) to the most advanced frontier of knowledge, skills and autonomy (i.e. level 8; Europass European Union, 2017).*

## Appendix H: Foundation for the AI qualification framework

| Profile | Potential difficulties with its access | Domain | Minimum level of EQF |
|---|---|---|---|
| **1) Data scientist**<br>*Multidisciplinary profile that combines computer science, statistics and mathematics.*<br><br>**2) AI developer company**<br>*Company specialized in the development of AI solutions.* | *Data scientist:*<br>- Observed scarcity in the market, companies are competing for its access.<br><br>*AI developer company:*<br>- No difficulties. | Data-oriented competencies | Level 4 |
| | | Technology-oriented competences | Level 5 |
| | | Industry-oriented competencies | Level 3 |
| **3) Hybrid profile**<br>*Individual who knows both the technology and the industry* | *Hybrid profile*<br>- Absence of a pre-defined profile. This role must be crafted within the company. | Data-oriented competencies | Level 1 |
| | | Technology-oriented competences | Level 4 |
| | | Industry-oriented competencies | Level 4 |
| **4) Expert end-users**<br>*Experienced individual within the department where the solution is adopted* | *Expert end-users:*<br>- No difficulties. | Data-oriented competencies | Level 1 |
| | | Technology-oriented competences | Level 2 |
| | | Industry-oriented competencies | Level 5 |
| **5) AI ethicists**<br>*Individual knowledgeable of the impact of AI within the business and society.*<br><br>**6) Lawyer**<br>*Individual that knows the legal framework which AI must respect.* | *AI ethicists:*<br>- Observed scarcity in the market, companies are competing for its access.<br><br>*Lawyer:*<br>- Observed scarcity in the market, companies are competing for its access. | Data-oriented competencies | Level 1 |
| | | Technology-oriented competences | Level 3 |
| | | Industry-oriented competencies | Level 5 |
| **7) Data quality manager:**<br>*Responsible for the identification, communication and assessment of data quality standards.*<br>**8) Data steward**<br>*Responsible of overviews regarding internal business* | *Data quality manager, data steward & data custodian:*<br>- No difficulties (professional services are available to help with implementing the fundamentals for data governance processes). | Data-oriented competencies | Level 5 |
| | | Technology-oriented competences | Level 2 |

| | | | |
|---|---|---|---|
| *processes and their data requirements.*<br>**9) Data custodian:**<br>*Responsible for data management plans and ensuring company's data assets.* | | Industry-oriented competencies | Level 3 |
| **10) Data architect:**<br>*Responsible to establish semantics and ensure the interpretability of data.* | *Data architect:*<br>- No difficulties (professional services are available to help with implementing the fundamentals for data governance processes) | Data-oriented competencies | Level 5 |
| **11) Analytic translator:** | *Analytic translator & business translator:* | Technology-oriented competences | Level 2 |
| *Responsible for the translation of business problems into analytic processes.*<br>**12) Business translator:**<br>*Facilitator of the first stage of AI project, namely business understanding.* | - No difficulties. | Industry-oriented competencies | Level 3 |

*Table 10: The summary of the content for the qualification framework resulting from the findings of this study.*

# Appendix I: CAP follow up questionnaire

1. How would you rate your experience during the activities organized within Module X of the CAP?

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |

Not satisfied — It was OK — Very satisfied

2. How can we improve this module for next year?

(free text box)

3. Do you think you learn something from the activities organized in Module X of the CAP?

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |

Not at all — A little — Very much

4. Who would you like to invite next time?

(free text box)

# Appendix J: Questions of the focus group

**<u>Part II (20 minutes):</u>**

- *Decision regarding which alternative to adopt*
    1. Before sharing your feedback on the alternatives, do you have any question related to their structure and requirements?
    2. Which alternative do you think the AIIC should adopt? Why?
- *Feedback & questions related to that alternative*.
    3. Where can I improve the chosen framework?
    4. Do you think that this roadmap helps the AIIC in providing access to technical qualification and pursue its vision?
    5. What can be improved in this roadmap

**<u>Part IV (20 minutes):</u>**

- *Feedback on the structure of the CAP*
    1. Before sharing your feedback on the alternatives, do you have any question related to the CAP structure?
    2. Do you think that the AIIC can provide these services in terms of resources?
- *Feedback on the contribution expected from the AIIC.*
    3. Do you think the content of the CAP should cover further topics?
    4. Do you think that the AIIC can provide these services in terms of resources?
    5. Do you think that the CAP helps the AIIC in creating awareness among potential customers?
    6. What can be improved within the CAP?

**<u>Final feedback:</u>**

1. Do you see the solutions just presented as tools to pursue the Center's vision?

## Appendix K: Final approach of the AIIC

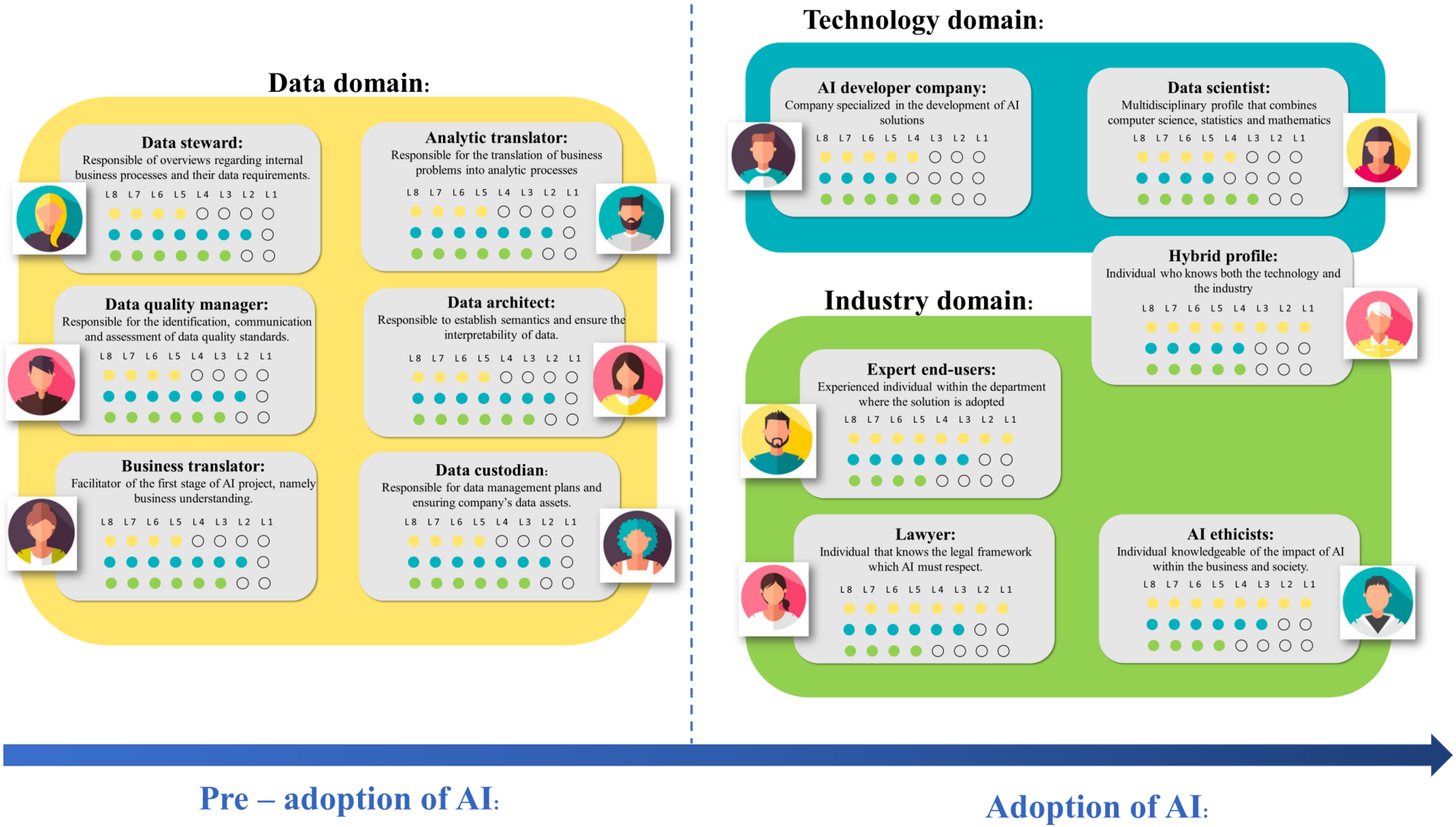


*Figure 27: The improved AI qualification framework that integrates the two alternatives proposed in section 6.1.2 as a unique option.*

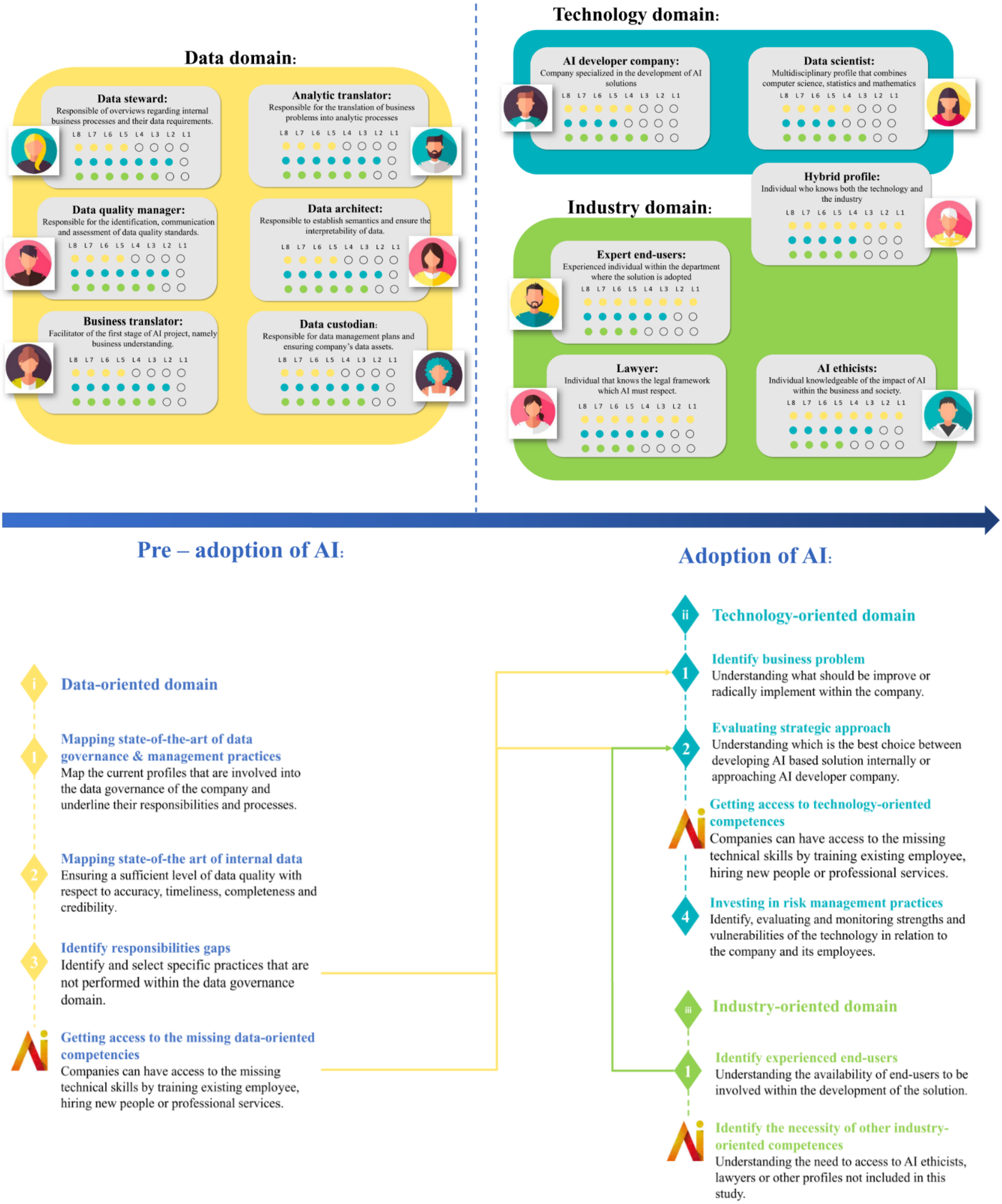


*Figure 28: The AI qualification framework displayed in a poster which will help the AIIC in better communicating with the customers.*

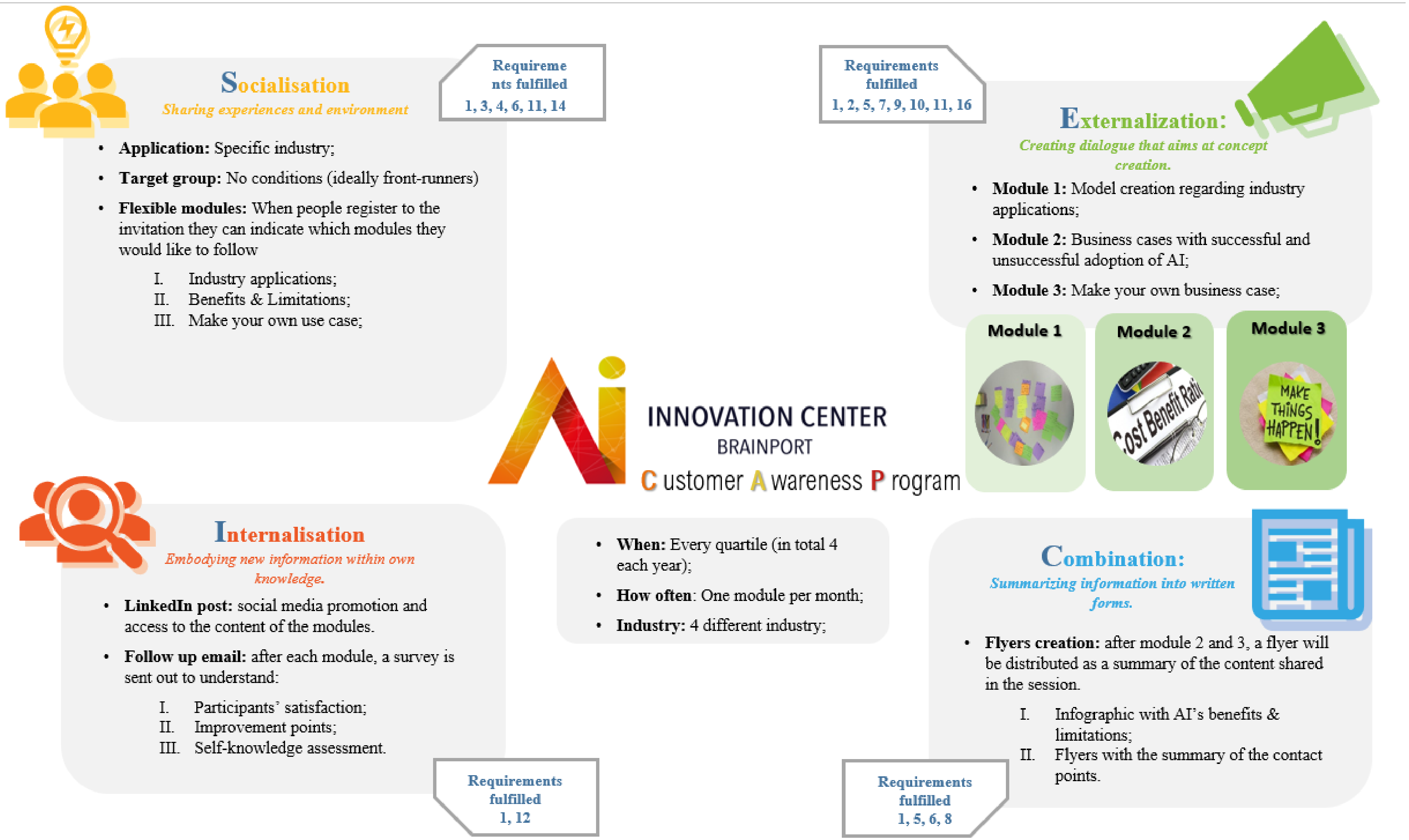


*Figure 29: The improved foundation of the CAP model including the feedback received during the focus group.*

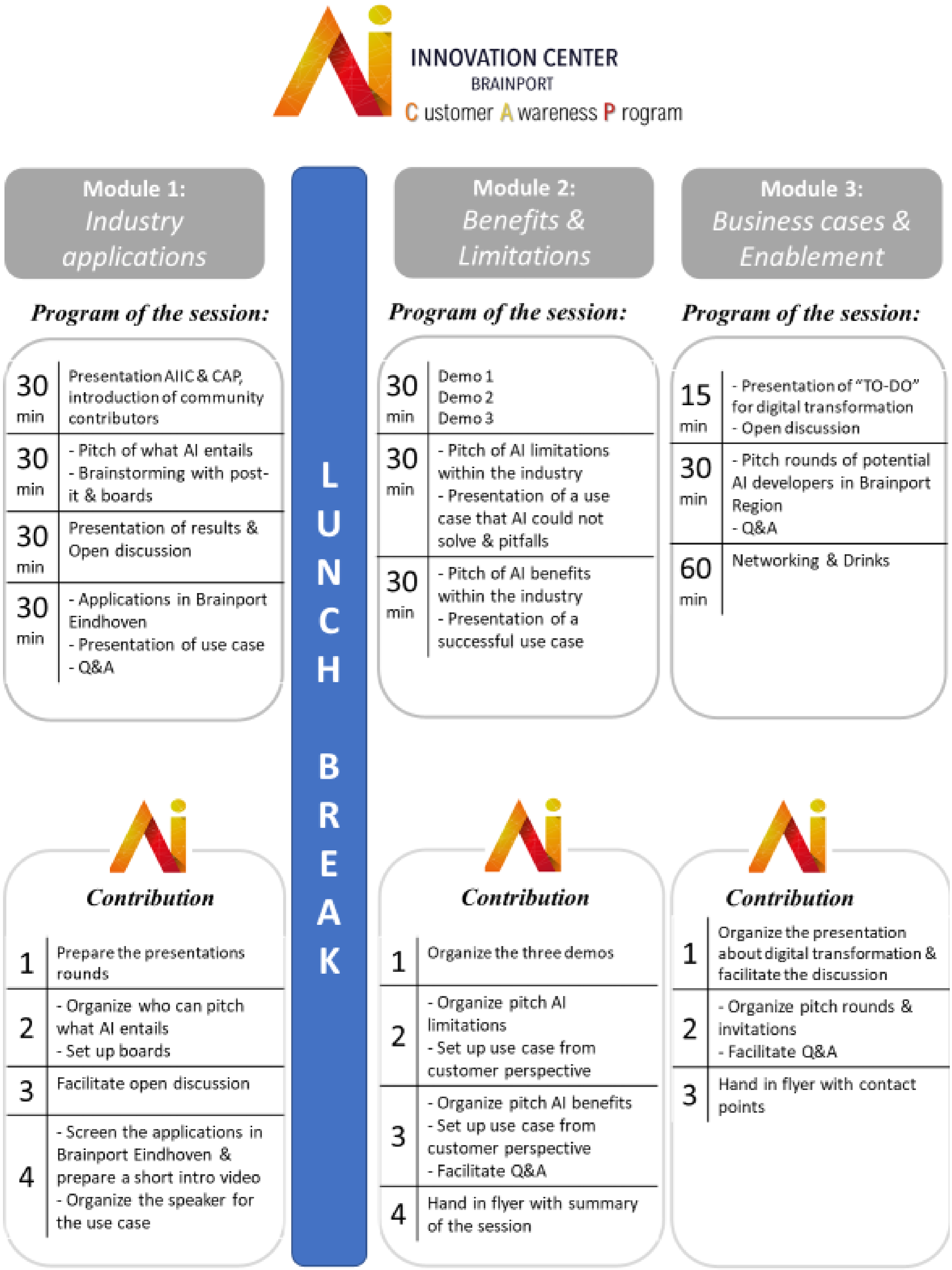


*Figure 30: The improved Customer Awareness Program (CAP) including the feedback of the focus group.*