# Exploring end-user acceptance and exploitation routes of industrial use cases related to AI and HMI

## -Evidence from the Lab and Field Experimental Approaches

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**Abstract.** In this position paper, we discuss how to explore end-user acceptance and to exploit routes of industrial use cases related to artificial intelligence (AI) and human-machine interfaces (HMI) by the lab and field experimental approaches. Through our three-stage process, we identify the market potential in AI and HMI areas and figure out our target customers with specific functions of robots. Besides, we verify our results from the lab and field environments to the real-market situation and get feedback from our customers.

**Keywords:** Artificial Intelligence, Market Potential, Target Market, User Acceptance Testing, Initial Trust, Target Consumers.

## 1 Introduction

In the past 60 years, many applications of artificial intelligence (AI) have been deployed in high-income country contexts (Wahl et al., 2018) since the term 'AI' was first coined by a group of researchers in 1956 (Knapp, 2006). Although Google-DeepMind's AlphaGo program triumphed in its final game against South Korean Go grandmaster Lee Sedol to win the series 4-1, providing further evidence of the landmark achievement for an artificial intelligence program (Borowiec, 2016), there are still some trust problems related to AI applications. In AI, an expert system needs to be able to justify and explain a decision to the user (Pieters, 2011). The trust is the key to ensure the acceptance and continuing progress and development of artificial intelligence (Siau&Wang, 2018).

Besides, self-driving cars, drones, and home robots are proliferating and advancing rapidly (Siau&Wang, 2018). In recent years, an increasing number of companies have been integrating AI technology and artificially intelligent robotic devices into their service, e.g. hospitality companies (Lin et al., 2019). Based on the market research from the firm Tractica, the global artificial intelligence software market is expected to experience massive growth in the coming years, with revenues increasing from around 9.5 billion U.S. dollars in 2018 to an expected 118.6 billion by 2025, including natural language processing, robotic process automation and machine learning (Liu, 2019). Therefore, there is enormous market potential in AI and human-machine interface (HMI) areas.

In this paper, we introduce the lab and field experimental approaches to test end-user acceptance and to investigate the market potential in AI and HMI in order to figure out our target customers and primary functions of products based on the market expectations. First, we design and conduct lab experiments to identify the target market and our target customers by recruiting university students. Based on the results at the first stage, we select several customers by conducting field experiments. Finally, we verify our results from both of the 1st & 2nd stages in the real-market situation and compare the expected market with the real market in order to promote our product to all potential customers.

## 2 State of the Art

Trust plays an essential role in helping users overcome perceptions of risk and uncertainty in the use and acceptance of new technology (Gefen et al., 2003; Pavlou and Gefen, 2004). One kind of trust is called 'initial trust' that is built based on an individual's disposition or institutional cues (McKnight et al., 1998), which is essential for promoting the adoption of new technologies (Li, 2008). Hence, both initial trust formation and continuous trust development should be considered in the context of trust in AI (Siau&Wang, 2018). There are three factors to determine trust in technology: (1) human characteristics (Hengstler et al., 2016), (2) environment characteristics (Oleson et al., 2011) and (3) technology characteristics (Schaefer et al., 2016). Siau&Wang (2018) analyzed technology characteristics from three perspectives: (a) the performance of the technology, (b) its process/attributes and (c) its purpose. Obviously, artificial intelligence has many new features compared to other technologies, from its performance, process, and purpose (Siau&Wang, 2018). Therefore, we could improve users' product acceptability by building initial trust in AI and developing continuous trust in AI.

According to Sirkin et al. (2015)'s paper, industrial robots first began to appear on industrial assembly lines in the 1960s. After that, robotic systems are fast becoming a viable economic alternative to human labour in many high-wage economies – though the cost-benefit trade-off varies across industrial sectors. In addition, the most advanced robots are also more intelligent in that they can provide and receive feedback to other parts of the production system. For instance, machine-to-human interaction will allow greater product customization (Strange & Zucchella, 2017).

Furthermore, a new type of business emerged called e-business containing e-signature, e-invoice, e-commerce, internet, mobile banking and e-payments with massive transformation, creating efficiency in corporate and individual life. Minimizing or optimizing the work processes, business processes reengineering shifted industrial age towards the digital age by the help of e-business environments (Dirican, 2015). The research of McKinsey Global Institute shows that a new generation of more sophisticated robots is becoming commercially available. These advanced robots have greater mobility, dexterity, flexibility, and adaptability, as well as the ability to learn from and interact with humans, greatly expanding their range of potential applications (Manyika, 2013). For instance, Dirican (2015)'s paper pointed out that agents in contact centres or tellers could be replaced by robots that are being supported and strengthened by artificial intelligence. Moreover, Wang et al. (2006)'s research gave evidence that the medical robotics marketplace is beginning to take hold, with an increasing number of robotic products that perform a wide variety of tasks.

## 3 Conceptualisation

In order to understand the end-user acceptance and the business development plans of AI-supported human-machine interfaces for personal health services in the European Union (EU) market, we have designed a three-stage process which during 36 months will explore end-users opinion, exploitation routes and market implementation of industrial use cases related to artificial intelligence, human-machine interactions and robotics in the context of EU.

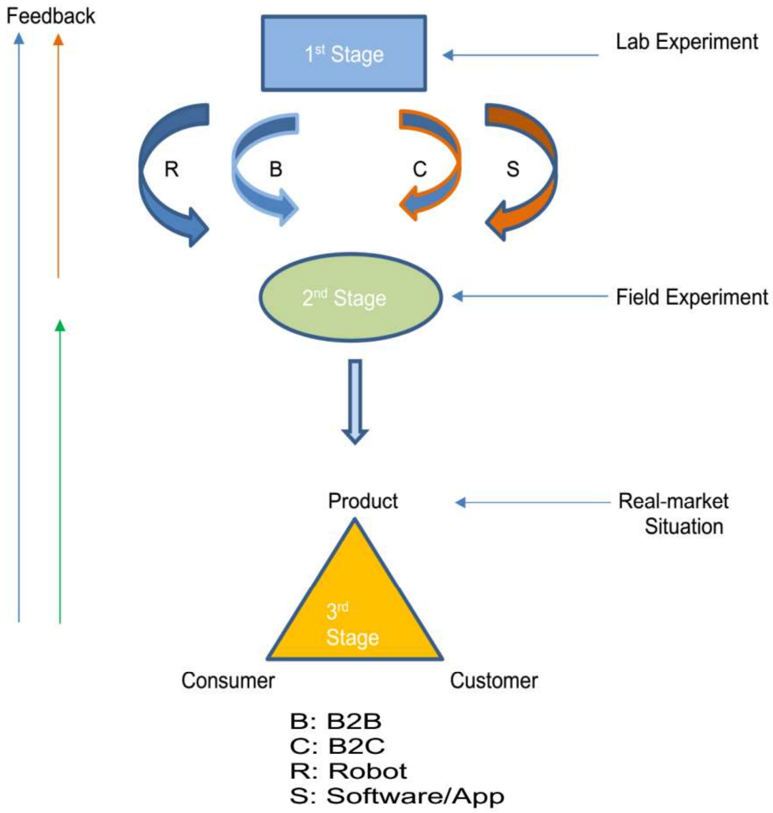



**Fig. 1.** The 3-stage scheme for exploiting business development plans related to AI and HMI.

### 3.1 Stage 1: Lab experiments

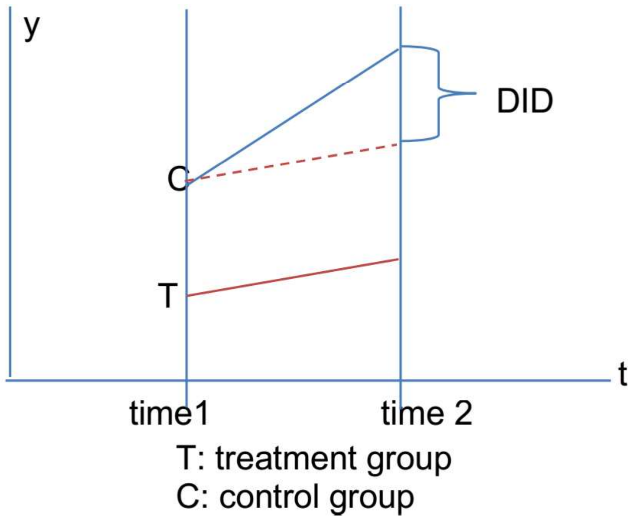
The purposes of the first stage are: (1) to distinguish the market potential whether on B2B market or B2C market; (2) to identify the market potential whether in the AI device area or the AI-supported software area.

We will conduct one lab experiment or a series of experiments by recruiting university students to track their behaviour (consumer behaviour) for more than one year. Through answering multiple questions and/or performing tasks under more than one external stimulus in this 'within-subject[1]' designed experiment, we could observe individual behaviour change with circumstances of the experiment changing (Char-

[1] In a 'within-subject' designed experiment, each individual is exposed to more than one of the treatments being tested. By contrast,each individual is exposed to only one treatment in a 'between-subject' designed experiment (Charness, Gneezy& Kuhn, 2012).

ness, Gneezy& Kuhn, 2012). In this way, we explain how consumer behaviour changes by changing the product price, the function of the product or the family income in the experiment. Moreover, students can quickly test different versions of our products from the first draft to the latest human-machine interface by 'within-subject' experiment. Besides, we will offer several pieces of training for our products for the same participants. Comparing the before-after differences, we verify whether the public understands our instructions for users by difference-in-differences (DID[2]) methodology. For instance, there are two groups with different levels of medical knowledge: medical students and students majoring in any other subjects. Medical students are selected in the control group, whereas other students join in the treatment group. If medical students perform significantly better than other students after the training, this training is not suitable for the public because of high-level knowledge.

**Fig. 2.** Difference-in-differences methodology in the experiment.




Last but not least, the participants will test similar competitive products. Taking the medical diagnostic and treatment software 'Ada[3]' for example, we will let the participants examine the software to find the market potential from the feedback of users. McDonald (2006) gave the distinction between consumers and customers. 'Consumers' signify a relationship in which welfare is seen as a product for the consumer, managed by a case or care manager who is accountable to the state and their manager much more so than to their profession or those using the service. 'Customers' signify

[2] The difference-in-differences (DID) estimator is one of the most popular tools for applied research in economics to evaluate the effects of public interventions and other treatments of interest on some relevant outcome variables (Abadie, 2005).

[3] https://ada.com/about/.

a marketization of social care wherein welfare is a commodity for the customer (McLaughlin,2009). Therefore, our B2C clients are considered as consumers of our products and B2B clients will be customers.

On the other hand, we will also recruit the students at the start-up centre[4] at universities, e.g. at the University of Cagliari to figure out whether there is market potential in B2B marketing.

### 3.2 Stage 2: Field experiments

Based on the first stage, we further our experiment to test our results from the lab experiment by joining community activities, design & conduct online survey and other partners' activities. Our B2B clients can be the hospital, insurance company, kindergarten & primary school.

#### B2B Marketing Strategies

We will cooperate with some partners, especially some doctors, to figure out the functions of our robots. For instance, if family doctors are not in the clinic, patients could still do some tests by using robots.

Besides, we will collaborate with other partners, especially insurance company, to figure out the functions of our Software& App, e.g. some online training/courses in the home healthcare and health self-management.

#### B2C Marketing Strategies

We will do some surveys or interviews, e.g. parents if we develop our robots in Mother&Child care (e.g. Philips uGrow[5]). In this area, we will collaborate with other PhD candidates and other institutions/partners could be involved.

Moreover, we will develop some software that already existed in the market with a large number of users, e.g. Ada.

### 3.3 Stage 3: Feedback from the real-market situation

Based on the first & second stages, we verify our results from lab & field experiments by online promoting and feedback from our consumers and customers, e.g. from par-

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[4] Students develop entrepreneurial skills and they are encouraged to start up their own company at the start-up centre.

[5] https://www.usa.philips.com/c-m-mo/ugrow-baby-development-tracker.

ents, doctors, the insurance company, etc. Besides, we will get the analysis of public opinion stance.

In this 3-stage scheme, we get feedback at each stage and also analyse any differences between the expected market and the real market situation.

## 4 Conclusion and next steps

With our research on acceptance and business opportunity of AI-supported human-machine interfaces for personal health services, we plan to understand consumer behaviour and to figure out the market potential.

We figure out whether to enter a new market by calculating the utility with game theory[6] methodology. In our case, we compare the utility in each situation.

| | |
|---|---|
| (B,R)=br | (C,R)=cr |
| (B,S)=bs | (C,S)=cs |

B: B2B
C: B2C
R: Robot
S: Software/App

**Fig. 3.** Game theory for entering a new market.

There are four preferences in the market:

1. B2B better & customers prefer the robotic device more than software, if br > bs;
2. B2B better & customers prefer software more than robots, if br < bs;
3. B2C better & consumers prefer the robotic device more than software, if cr > cs;
4. B2C better & consumers prefer software more than robots, if cr < cs.

In addition, customers (B2B) care about the Return on Investment (ROI):

$$ROI = \frac{Current\ Value\ of\ Investment - Cost\ of\ Investment}{Cost\ of\ Investment}$$

Hence, the price of our products will be an essential factor for our customers. On the contrary, consumers (individuals) will focus on the performance/function of products.

6 Game theory is the study of mathematical models of strategic interaction among rational decision-makers (Myerson, 1991).

By experimenting, we conclude through models of experimental economics & game theory. Using statistical techniques such as panel data and DID[7], we get a quantitative analysis of the market potential.

Based on our research, we will narrow a target market and focus on our target consumers/customers to design and develop the next-generation product. After the next generation is completed, we will repeat the 3-stage process to do product modification based on user experiences.

In this way, we will find the specific function of our robots/software for certain consumers/customers.

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[7] The difference-in-differences (DID) estimator is one of the most popular tools for applied research in economics to evaluate the effects of public interventions and other treatments of interest on some relevant outcome variables (Abadie, 2005).

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