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Expanding the frontiers of design: A blessing or a curse?

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The designer as cross-boundaries mediator: Merging machine learning, ethics, and design for the flourishing of humans

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Abstract. Designers are elusive figures to define. As human beings, they have the ability to conceive and/or create something for a purpose, yet they are characterized by empathy, system-level thinking, and a transformative influence on the world: features that enable them to tackle significant challenges. To achieve high goals, though, they need to navigate across disciplinary boundaries, building on diverse disciplines theories and approaches to complement their education and to frame and address complex problems adequately. Among them, machine learning (ML) knowledge and ethical perspectives could be essential materials to face contemporary issues and design for the flourishing of humans and their ecosystems. In the following, a didactic experiment (i) to provide design students the tools to understand and exploit ML by translating technical knowledge in a designerly way, and (ii) to frame their education in a value-sensitive design perspective is described and discussed.

Keywords: expanding design education, introductory ML design game, machine learning (for) design, research-through-design, responsible design

1 Introduction

1.1 Everybody can design, but what defines a designer?

Prehistory is marked by the rise of technology: the first rudimental tools that men created. Indeed, if we consider design in its broadest sense, as the act of conceiving and/or creating something for a purpose, this capability – diffuse design in the words of Ezio Manzini (Manzini & Coad, 2015) – has characterized humankind since the beginning of time. Then, it might not surprise if different disciplines are now adopting and appropriating some design skills because, in the end, they belong to all of us.

In narrowing down today's role of designers, it quickly becomes clear how much it is or should be expanding across boundaries but maintaining an undoubted specificity.

Throughout history, designers have been identified as the professionals who care about the beauty and the appearance of things, or as those focusing on their function, yet, going to the very roots of the practice of design in its multiple forms and embedding the viewpoint of activity theory (Kaptelinin & Nardi, 2009), we may say that what primarily define designers is their capability to mediate between humans and the world. Based on what they have available, they can envision things that have never existed before and create something valuable both in a concrete and an abstract sense, spacing between different scopes, which makes design a pervasive activity (Louridas, 1999). Especially from this point, the current figure of the designer needs to be reshaped in the eyes of the lay public as well as within the disciplinary educational institutions.

Designers' main value lies in their ability to transform the world according to a predefined purpose (may this be for pleasure, better usability, or survival). Hence, they can easily adapt to different contexts, and it gives them the possibility to play critical roles in today's pressing issues: either to

solve problems, no matter how ill-defined they are, but especially to frame them correctly thanks to their systemic reasoning.

In fact, more than ever before, we are becoming aware of the challenges we are facing, and that may increase in the near future. Friedman (2019) even listed a set of specific challenges for design that span throughout all levels of human condition: from performative issues to systemic, contextual, and even global challenges (M. W. Meyer & Norman, 2020). What emerges from the authors' perspective is the necessity for designers to work across disciplinary boundaries to actually pervade and contribute to any sort of issue we are called to respond to, not only by being incrementally involved in multidisciplinary teams but also by taking on organizational and managerial positions.

1.2 Building the cross-boundaries mediator

In this historical moment, we are assisting to the revival of artificial intelligence (AI) and – more prominently – machine learning (ML) systems, which are wildly spreading into everyday life, due to the favorable technological development (i.e., improved computational power and availability of large amounts of data) and are expected to have significant impacts on human life as electricity did (Kelly, 2016). Dating back to the 1950s, AI is the field concerned with building machines "that can compute how to act effectively and safely in a wide variety of novel situations" (Russell & Norvig, 2020), and ML – its most popular subfield – is getting a lot of attention as it allows to create systems that address uncertain issues (i.e., for which writing step-by-step instructions would require a great effort or may not be possible) only by giving them a specific goal and huge amounts of examples to learn from, to finally let them derive how to reach the goal and improve their performance over time. In practical terms, it means that, among several other ML applications, it is now possible to easily automate burdensome and repetitive human tasks, personalize contents according to people's preferences and behaviors, interact with devices by using natural language, and infer information from massive quantities of data. The main issue, though, is that the technology-driven diffusion of ML systems often is not in line with people's needs, desires, or expectations. It does not comprehend the "wholeness of humanity" (Antonelli, 2018), while design has the potential to address this matter in a human-centered way. Therefore, this field may be a perfect playground for designers, who have the skills to anticipate the impacts of a technology and to provide it new meanings, but, unfortunately, they seem unprepared to effectively leverage ML capabilities and foresee opportunities as they lack understanding, experience, tools, and methodologies to deal with it (Dove et al., 2017; Yang et al., 2020).

Thus, besides a revised definition of their role (as suggested in 1.1), designers need to be given suitable means to amplify their field of action and have a role in this current hot topic. Specifically, as Meyer and Norman (2020) report, design education should "draw more extensively on knowledge developed in other established fields, translating that understanding into a form useful to practicing designers."

To support the argumentation, the paper proposes an example of expanding the borders of design across disciplines by merging ML knowledge, ethical perspective, and traditional design skills (like empathy, system-level thinking, and a transformative influence on the world) to enable designers to impact human life. Indeed, ML could benefit people and their ecosystems in a revolutionary way as it unveils whole new possibilities to interact with the world, and, according to their defining traits presented above, designers have the potential to steer the spreading of this technology towards beneficial outcomes and trigger unexpected innovation if given the possibility.

The experimentation stems from a research project aimed at providing future designers the essential skills to navigate across disciplines in order to design responsible and meaningful systems integrating ML. Specifically, it is developing a methodological contribution for MSc design education and

designerly tools to enhance cross-fertilization and interdisciplinary communication between design and ML, with a research-through-design approach.

Two are the main features of the proposed activity: (i) providing design students the tools to understand and exploit ML by translating technical knowledge in a designerly way, and (ii) framing their education in a value-sensitive design perspective (van den Hoven, 2013).

As a matter of fact, it is in the light of awareness and responsibility – about technological potential and limitations as well as about ethical and sociological implications – that designers can play their mediating role to address the criticalities of human life.

2 An experimental method for expanding the frontiers of design

2.2 Setting up the didactic activity: aim, target, and modalities

Even though some attempts to bring AI/ML (Futurice, 2017; Piet, 2019) and ethics (Artefact, 2017; Gispen, 2017) to designers are emerging, to the best of the author's knowledge, this represents a first empirical experiment on merging together the three disciplinary perspectives on ML systems development. Specifically, the study aims to assess the response of designers to this multifaceted topic. Configured as an introductory didactic activity to present the core ingredients of ML as design material, it targets doctoral students with some or no prior knowledge of the subject matter. They are relevant testers because they are close to the intended audience for the research, and they have more analytical skills, didactic experience, and consciousness about design research theories and methods to build an insightful discussion and peer-evaluation of the activity. Further iterations and applications may also involve MSc design and engineering or computer science students.

The expected impact of this activity is to build awareness on the ML topic and pave the way towards a value-sensitive approach to designing ML-infused solutions. For this, the set learning outcomes include that: (i) in terms of knowledge, students should gain familiarity with the basic capabilities, limitations, and implications of ML systems, as well as the main values and possibilities for a responsible and trustworthy design. (ii) In relation to skills, they should learn to pursue a value-driven design process, activate fruitful discussions in team collaboration, and identify ML as a design material. While (iii) concerning values, they should understand how to be responsible designers in the contemporary situation and that ML can be an asset to face big challenges.



Figure 1. In-presence playtest. Photo by the author

Due to its introductory character, the activity has been imagined as a brief (one to two hours) and engaging experience, possibly anticipating a more extensive didactic path. Thus, a cooperative board game format seemed the perfect fit to gently introduce the main topics, give procedural information, and stimulate reflection and discussion in a practical context. In fact, games create a parallel world, a safe place in between the physical and the game dimension itself (Huizinga, 1938), where players can freely express themselves, make mistakes, and learn with no concrete repercussions. The cooperative nature of the game, in this case, is essential as collaboration amplifies the team dimension that characterizes a design environment (to which the participants are used) and naturally encourages discussion and exchange.

As the pandemic period requires, the activity has been developed and tested with both physical and digital supports in two different sessions, each with two Ph.D. design students, for a total of four participants. For the qualitative purposes of the research, the limited number of testers left enough space for the involved people to actively interact with the game and freely express their reflections, and it allowed for an in-depth look at the experience of the activity itself, but of course, this presents some limitations in terms of representativeness.

The first in-presence session (Fig. 1) involved two students with no prior knowledge of the subject matter. For the second one, instead, the selected Ph.D. students' research areas are somehow related to ML as a technology. For this session, the Miro platform (Fig. 2) has been chosen as digital support because it effectively enables most of the actions that they would have performed in live collaboration.



Figure 2. Overview of the digital board supporting the online activity. Created by the author

2.3 An introductory board game: theory, tools, and procedures to structure the activity

As the focus of the activity is to push designers to the edge of disciplinary boundaries to embrace and mediate between designerly approach, ML contents, and ethical perspectives, the design process represents the perfect space for the combination of the three ingredients. In a preliminary analysis (Fig. 3), the author explored how the three disciplines could contribute to each of the five stages of the

design thinking process, as illustrated by (Dam & Siang, 2021). The ideation phase resulted in being the one in which the mergence is most functional and significant. Therefore, the whole game explicitly refers to it.



Figure 3. Autor's analysis of disciplinary contributions at each stage of the design thinking process

SET-UP. The initial situation presents the players with their role as designers at the service of a fictional World Association for Challenging and Strategic Issues (WACSI). They are called to join and lead a team with the aim of designing a system to accomplish a given mission. Before starting, an *impact goal* and a *key outcome* – as intended in (Design Kit, n.d.) – with available datasets are provided to synthesize the mission. The *impact goals* – long-term, significant impacts one is working to achieve – are identified as the Sustainable Development Goals (SDGs) of the United Nations (UN - Open Working Group, 2015) and declined with one of their more precise targets. While the *key outcomes* – near-term and observable change/behavior one wants to promote – are defined to narrow down the problem, including information about the context and target audience.

Hence, this opening contains the basic assumptions upon which the research is built and intended for the participants to internalize: in the near future, designers striving for human flourishing should face increasingly dynamic and complex challenges (Weil & Mayfield, 2020). To this end, human needs will extend to a societal and eco-systemic dimension, and solutions will involve cutting-edge technology – an approach that influential academics called DesignX (Friedman et al., 2019).

After the initial setting, players are introduced to the core of their mission: to design a system, enhanced by ML, to beneficially impact the current situation according to their given purpose. The overall game structure aims at outlining the main steps one should follow to responsibly design a ML system, and it develops in three main phases: the *kick-off*, the *system design*, and the *weighing up*.

KICK-OFF. Preliminarily to any concept construction, few elements should be considered and openly defined to drive the ideation process. According to a value-sensitive design approach (van den Hoven, 2013), shared values should be expressed from the very early stages to be embedded in the technology and affect affordances and constraints of the system. Additionally, thinking explicitly about the values is morally significant and may lead to meaningful results. Hence, the players are invited to select one (i) *value* that will drive their system. Of course, it should not be the only one embedded but the most prominent one. The values proposed (Fig. 4) are an adaptation of the ethical principles behind the European Guidelines for Trustworthy AI (High-Level Expert Group on Artificial Intelligence, 2019b), which are highly comprehensive and founded on fundamental human rights. They are: respect for human autonomy, attention to fairness, increase of intelligibility, prevention of harm, and promotion of flourishing. The latter has been added in antithesis to the previous one to suggest a more proactive attitude towards life, well-being, growth, progress, and prosperity; while intelligibility replaces explicability because it implies that clarity can be achieved either by explanation or intuitively, expanding its sense to include UX issues as well.

VALUE	VALUE	VALUE	VALUE	VALUE
RESPECT FOR HUMAN AUTONOMY	ATTENTION TO FAIRNESS	INCREASE OF INTELLIGIBILITY	PREVENTION OF HARM	PROMOTION OF FLOURISHING
People must be free to make their own decisions and to take control	People and their ecosystems need to receive Just and impartial treatment, respecting a balanced proportionality between means and ends	Immediacy and understandability have to be guaranteed, whether with a proper explanation or intuitively	No material or mental damage has to be inflicted to people and their ecosystems, nor existing ones have to be worsen	Life, well-being, growth, progress and prosperity of eccosystems should be fostered and nurtured

Figure 4. Value cards provided in the game. Created by the author

Other essential components relate to the material at hand: ML systems. Their most common capabilities are introduced and synthesized in the form of (ii) ML agents. They represent the keystone of knowledge transfer. As in (M. Meyer, 2010) argumentation, they are conceived to be functional to move pieces of knowledge from one field to another by transforming it into a more familiar language for the recipients. Indeed, the characterization of ML systems as agents is actually borrowed by (Russell & Norvig, 2020), a worldwide reference textbook for AI – and, while maintaining technical correctness and clarity on their computer nature, an emphasis on the parallelism with human agents helps designers understand how to approach them as part of larger systems. Each ML agent embodies a ML task – or problem in the words of (Russell & Norvig, 2020) – and summarizes the question: what is the basic functioning principle of the system, generally speaking? The key tasks presented are classification, regression, sequence prediction, generation, clustering, and action selection – the explanation of which is beyond the scope of this argumentation. A previous workshop, organized in collaboration with a MSc student in Digital and Interaction Design at Politecnico di Milano (Arnone, 2020), proved this level of information, in-between the technical construction and the contextual capabilities of ML systems, to be essential and sufficient to enable design students to exploit this technology in concept elaborations effectively. The same experience revealed that a formal yet simplified definition of a ML system (summarizing its internal process in terms of input, procedure, and output) combined with case studies provide enough information for operational comprehension. Therefore, the ML agents sheets (Fig. 5) include a synthetic question expressing the core of the task, a brief definition, some system's contextual capabilities to exemplify current applications, and two case studies (a positive one that complies with SDGs-level challenges and a questionable one, threatening ethical principles).



Figure 5. Example of a ML agents sheet. Created by the author

Finally, the players are supplied with (iii) five general *intents* to beneficially impact human life (Fig. 6) – automate, augment, empower, inspire, and specialize – among which they should choose the one responding to the question: "how would your system improve the current situation?"

Then, *value*, *ML agent*, and *intent* constitute the proposed founding material to orientate the design process and outline a meaningful and responsible solution. Their initial definition is aimed at stimulating reflections and at keeping the team aligned on the same principles. It does not need to be permanent; instead, variations are part of an iterative process.

INTENT	INTENT	INTENT	INTENT	INTENT
AUTOMATE	AUGMENT	EMPOWER	INSPIRE	SPECIALIZE
Relieve people from tedious chores by doing tiresome, unstimulating and repetitive tasks for them	Extend human capabilities, by providing complementary functions or information	Enable people to do something otherwise impossible with just human capabilities	Instill some feeling and stimulate people to take action by presenting a new, interesting perspective	Give people support to help them become experts in a precise task or domain

Figure 6. Intent cards provided in the game. Created by the author

A limitation of this approach is that players are forced to include one *ML agent* in their design for the didactic purpose of understanding them through a direct application in a concrete example. This does not imply that ML is the preferable solution to any problem and neither that a single *ML agent* is enough to tackle complex tasks nor cannot work in cooperation with others. Unfortunately, as the activity pursues immediacy, a short time frame, and a playful format, these issues are just briefly mentioned, and a proper explanation does not find place in the game. Nevertheless, it should complement the educational path.

SYSTEM DESIGN. Once the *kick-off* phase is concluded, and the consequent foundational elements have been selected – always with the mission goals in mind – the backbone and the boundaries of the system to design should be clear. Indeed, the discussion for the selection should embed the envisioning of possibilities. That being the case, the elaboration of a more defined concept should be relatively immediate by following the established guidelines. Thus, for this activity, a time limit of five minutes is provided to avoid redundant overthinking, and the completion of a *system sheet* is

required. The latter should support the participants in formalizing the system's structure by pointing out its characterizing features. Specifically, it follows the configuration of the case studies attached to all the *ML agents* (as well as their definitions) and asks designers to describe: (i) the system task – how the *ML agent* should help to reach the goal; (ii) input – what information should the agent be supplied with to perform the task; (iii) output – what the agent is expected to give in return; (iv) stakeholders – who need to be involved in the team to set the right premises. Actually, (i), (ii), and (iii) are the basic constituents of any artificial intelligence (AI) system as outlined in the definition of the European Commission (High-Level Expert Group on Artificial Intelligence, 2019a). Instead, the identification and potential involvement of stakeholders in the design process is not only a widely suggested ethical practice but also a consolidated approach in the field of design (participatory design, or co-design). Ultimately, to anticipate possible difficulties in the systematization of the idea, examples have been prepared for the players to compare or adopt once the time is up. After the comparison, final adjustments can be made before moving on to the closing phase.

WEIGHING UP. Among morals, meaningfulness, and usability, the last part of the game encapsulates the human-centered soul of the approach. It introduces the criticalities that may emerge in a ML system, presenting them – in the form of cards – as the *concerns* raised by the fictional WACSI wise council. Each card (Fig. 7) includes a possible limitation of the system and the related implications, values, and options that designers have to avoid such hindrance. The *concern cards* are distinguished by disciplinary competence: some issues may be primarily identified or handled by ML developers, some by designers, and others by ethicists or social scientists. Still, they share the common goal of benefiting human beings and the world around them.

Concerns rooted in ethical discussions, which constitute the largest part of the deck, are the result of the analysis of the existing ethics guidelines comprehensively collected in the AI Ethics Guidelines Global Inventory (Algorithmic Watch, 2020). Currently, it includes 173 guidelines, among which only those in English, belonging to certain sectors, addressing AI in general (not specific applications such as AI in healthcare), and listing some principles AI systems should embody were considered to derive relevant values, implications, limitations, and options for the cards. As a result, 51 guidelines were selected: 7 from academia, 20 from civil society, one from intergovernmental organizations, one from international organizations, and 22 from the private sector. Further references include some consistent tools (Artefact, 2017; Calderon et al., 2019; Futurice, n.d.; IDEO, 2019) and the research work developed in the project Meet-AI for UX concerns (Spallazzo et al., 2021).

Moreover, time is another significant variable for facing concerns. Whether they occur during the design, development, or use of a ML system, a responsible approach requires that they be addressed early in the process, both to prevent risks and to avoid late and costly interventions. To highlight this point, the concern cards have been divided into three categories according to when the cause of concern is originated. In the *before use* deck, the cause of concern precedes the model creation (then the implications are patent also before the development of the system is complete); in the *in-use* deck, the cause of concern affects the use of the system; and in the *long run* deck, it develops over time.

With the purpose of stimulating discussions about possible unforeseen outcomes and reflections on responsible practices to be accounted for already in the ideation phase, the ultimate part of the game makes the players address up to nine different *concern cards* (three from each time category) randomly drawn. They can be read and solved in any order to underline that there is no preferable procedure as long as all kinds of issues are well pondered.



Figure 7. Example of a concern card. Created by the author.

As anticipated, all the cards present the readers a possible action that they can handle to increase the beneficial impacts of their system or that they can disregard, exposing the system to be a potential threat. Of course, not all the concerns apply to the imagined system or are preferable to comply with. The focus here is on balancing the possible good or harm a system can cause, keeping into account the time factor (time will not be sufficient if all options are fulfilled, as tackling all concerns in a project would be an endless work), and acting accordingly. To do so, players can add some notes to their system sheet (if necessary), replace any of the *value*, *ML agent*, or *intent* cards (optional, this action that would cost time), and advance a marker on the *benefits* and *time* indicators if they decide to address the concern, just move the *benefits* marker if they considered the issue before reading the card, or advance on the *threat* indicator when they decide to ignore it. Instructions about the movements of the markers are provided on the cards and vary according to their potential impact.

MISSION END. The end of the game is declared when players solve all the concern cards or reach the final space of any indicator (getting to use all the time at their disposal or attaining the maximum amount of benefits or threats). The level of positive or harmful impact achieved by the designed system determines the completion of the mission. Four different epilogues are available (Fig. 8), though they all converge in presenting the fundamental requirements for responsible innovation that students can guard for future reference: being (ethically) acceptable, sustainable, and socially desirable (von Schomberg, 2013). Ultimately, the game results in leaving open space for further considerations. In fact, whether a system satisfies these requisites – regardless of the outcome of the mission – is up to the players to understand and hopefully discuss.



Figure 8. Available mission end cards. Created by the author

3 From theory to practice: discussing the development of the game and the playtests

In the following, the results emerging from the observation of the playtests and the subsequent semistructured interviews on the translation of ML and ethics concepts for designers are discussed. The aim is to highlight the issues that affect the didactic purpose of the activity, while insights about the game materials and mechanics are beyond the scope of this argumentation.

3.1 Limitations: Where the translation needs refinement

Since it was a first tentative experimentation of merging three disciplinary perspectives to pursue a common goal, the playtests have been a very informative occasion to spot some weaknesses in the instructional framework.

Above all, conveying ML's value as a design material that can help facing important societal issues seemed feeble. In the first session, the *impact goal* was not made explicit as one of the SDGs, although clarifying that in the second playtest did not change the participants' perception. In fact, being Ph.D. students in the Department of Design at Politecnico di Milano, they are quite used to deal with such high goals. Certainly, *ML agents* were embraced in both sessions as manageable tools to address the mission, regardless of the scale of the problem.

Their communication, however, highlighted some difficulties. Even if the combination of a definition and case studies effectively delivered the core principles and the level was appropriate, the first impact with a technical presentation was a little disorienting for the players with no prior knowledge. At the same time, a more visual language could enhance assimilation and memory. The most problematic point, though, is the length of *ML agents* sheets. Although containing just essential information, they require some effort from players. If introduced in the *kick-off* phase, they break the rhythm of the activity, but also making them anticipate the game (as tested in the second version), it remains a burdensome task. A collective introduction, aided by visual supports, may facilitate the knowledge transfer, leaving *ML agents* sheets the role of reminders.

Similarly, the tone of the *concern cards* needs simplification for greater accessibility by master students (the ultimate target of the activity). Additionally, marking the differentiation of the cards' contents (limitations, implications values, options) may increase the intelligibility of the translation.

Overall, the game experience appeared balanced with respect to the capabilities of the testers and the provided knowledge. Some uncertainty emerged only in the *system design* phase of the second playtest when prior (non-expert) familiarity with the topic brought up issues that went beyond the intended task. This was a further indicator that expert assistance is essential at this stage of the game

development. Of course, some minor graphic adjustments might smooth out the fruition. Indeed, the order of the contents on the board has been modified for the second digital playtest to limit external intervention, increase the focus on each phase of the game, and the visibility of important definitions that the participants should acquire for a precise understanding of the elements in play. Though some confirmations by the facilitator were always sought, and the two-pages rules booklet predominantly guided the players, who quite ignored the additional contents on the board.

3.2 Challenges: among unexpected outcomes and space for improvement

The premises of this experimentation reveal its ambitious nature. Merging ML, ethics, and design in a single brief activity to start expanding the borders of current design education necessarily required simplification. After having identified the key information to be transferred within the didactic introduction, the risk of trivializing or omitting some fundamental pieces of knowledge was high because this translation represents quite an unexplored territory.

The problem is exemplified by the fact that ML systems are rarely linear and often necessitate integrating multiple systems to achieve seemingly simple goals. More *ML agents* may be combined to get to a solution, yet the players are asked to select only one and describe the system accordingly. Although this helps limit the time and complexity of the activity by encouraging novices to focus on one agent at a time, it lacks completeness. In fact, some confusion arose during the second session system design phase. In this case, the participants aimed at building a recommendation system to orient potential criminals towards positive activities instead of perpetrating in noxious environments. To do so, they identified the Sequence Prediction (SP) Agent - able to predict values or outcomes in a sequence based on historical information (data in which it is possible to detect patterns of activities or behaviors over time) – as means to reach their goal. As visible in Fig. 9, they wanted to feed the system with twofold sequential data: sentiment analysis of posts on social media (like Facebook) and videos and ads of constructive activities capable of capturing users in a virtuous circle. Though, to produce both kinds of information, other ML agents are necessary: specifically, a classification system able to determine whether hate or violence emerge from written posts (to detect which people to target with positive contents), and another one to identify contents that instill positive addiction towards constructive subjects (to decide which suggestions the SP Agent might propose). At this point, the recognized overlapping of sequence prediction and classification tasks induced a short circuit and required the facilitator's intervention. Yet, to understand the basic principles of ML, is it necessary for the ideated systems to be totally correct, or are some mistakes allowed in favor of immediacy?

The example highlights how the gradual expansion of the frontiers of design has to be reasoned thoughtfully: the completion of the system design sheet leverages consolidated design skills, but the modalities of knowledge transfer may challenge the process.

How?	Input		Output	Stakeholders
by redirecting the attention of potential criminals behavior towards life opportunities	sentiment analysis of social media platforms (FB)	constructive activities and interests (cats)	purified feed	Behavior Design Lab Models and Methods For Behavior Change

Figure 9. System design sheet developed in the second playtest

Another central issue is enabling the participants to elaborate on a system concept by integrating the multidisciplinary perspectives acquired. It affects both the framing of the ML problem for the *set-up*

and the *system design* phase. In the *set-up*, defining the *key outcomes* that players need to reach with their systems means finding a balance between specificity and freedom. In the first case, the *key outcome* should be very detailed and imply only one ML solution; in the latter, it would be broader, leaving space for several possibilities (maybe not straightforward or not involving ML). Another concern that can be raised is that forcing a ML-infused solution could suggest a technology-driven approach. For the *system design* phase, the focus is on the guidelines for an actionable *system design* sheet: they need to be easy to understand and follow, and, ultimately, they should empower players to depict a system in both a sufficient but not too detailed way.



Figure 10. Key outcome and impact goal cards on the board. Created by the author

Since the activity entails the total inexperience of the students in designing with ML, it was challenging to understand which level of guidance they might need with the few tools provided. In the end, to measure the capabilities of the testers, the *key outcome* cards (Fig. 10) contained only quite general briefs and suggested datasets (as possible inputs for the system to design), while sample sheets were prepared and included in the game as a backup plan. The *system design* sheets, instead, were supported by the structure of *ML agents* ones. Surprisingly, during both experiences, the participants had no trouble in quickly delivering a system idea. The suggested datasets in the settings and the examples after the *system design* activity were not even necessary (in fact, the latter were not included in the second playtest, which caused no problem). Instead, the case studies from the *ML agents* sheets were important references to comprehend the requirements properly. However, what needs to be clarified is whether the systemic vision of Ph.D. students may have affected these results or if it also applies to master-level students.

Eventually, the playtests revealed some challenges also in the *weighing-up* phase. Although they had the chance to modify the elements defined in the *kick-off* (*value*, *ML agent*, *intent*), this was never considered. On the contrary, deciding to address a concern was so easy to comply with, while ignoring it caused negative feelings. Especially in the first session, the cards were perceived as prescriptive and triggered reactions like: "How to say no?" In this light, the purpose of the *weighing-up* phase could be reinforced towards a more conscious and thorough questioning of the idea. Then, instead of having students acknowledge some possible concerns about ML systems, the *concern cards* could be reframed to go deeper into project matters, stimulating a more realistic iterative process.

Overall, the main challenges for enabling designers to work across disciplinary boundaries lie in the interstitial points between them, more precisely in knowledge transfer and operationalization. Especially in the introductory phases of a disciplinary expansion, trade-offs are required: it is necessary to understand what the most appropriate levels of completeness, depth, guidance, and active involvement with the contents for designers to deal with are.

3.3 Strengths: Rudiments for a hybrid designer

The enthusiast exclamation "I learned something today!", pronounced by one of the participants at the end of the game, perfectly synthesizes the most valuable outcome of the didactic experience. Indeed, testers in both sessions proved and confirmed that they had finely assimilated the pieces of knowledge that the activity aimed to instill, despite the substantial cognitive load to which they have been exposed. Moreover, the connection of the three disciplinary perspectives was discerned, and the participants demonstrated no problems in handling them, proving their openness towards expanding the frontiers of design.

In fact, despite the aforementioned issues with the dense contents of *ML agents* sheets, all the Ph.D. students involved in the experiment appeared at ease with the given materials and tasks, and these were effective in providing the basic equipment to face the system design. For instance, in this sense, the custom additions to the values and intents usually encountered in the literature received very positive feedback and have been incorporated into the system's foundations (Fig. 11). In fact, towards the *key outcome* of preventing deadly attacks orchestrated by organized crime in public spaces, both groups embarked on a proactive approach. The first one elected *promotion of flourishing* as driving value because it was considered more comprehensive than *prevention of harm:* they stated it could help people appropriate their territory and avoid crimes. The second chose *inspire* as system intent to encourage potential criminals to pursue constructive interests.

Already during the *kick-off* phase, several ideas were brainstormed, triggered by an effective combination of ML agents' capabilities, intents, and values, so that the design of the system flowed smoothly. Also, to define the trickier elements (i.e., input and stakeholders), the players needed no assistance and identified coherent and original ones.

Additionally, from the very beginning, ethical concerns were explicitly discussed, as value-driven design may already be embedded in the mindset of designers. Indeed, this was the case for both the Ph.D. students with no prior knowledge of ML and for those who might have been exposed to this subject. The former imagined a detector of the conditions that nurture crime (given context and municipality investments), insisting on including different stakeholders for a plural perspective. The latter proposed a recommendation system to deter criminals from malicious activities and drive them towards more constructive ones. In this case, the players were perfectly aware of their system's insidious and manipulative nature, though they considered this solution more ethically acceptable compared to capillary and undifferentiated surveillance. Therefore, even without a formal ethics education, the Ph.D. students manifested a responsible approach to design. Being early-stage researchers, their sensitivity may be increased; still, these kinds of considerations are at the basis of human-centered reasoning.



Figure 11. Selected elements for the kick-off phase in the in-presence (above) and online (below) playtests

Albeit the expected outcome of enabling students to activate fruitful discussion should be verified in less guided contexts, the cooperative game turned out to be a fertile ground for debate and represented a successful example for opening the frontiers of design and enriching its tools. Throughout the entire activity, in both the physical and digital environments, communication is effectively fostered by the materials and the assignments players are faced with. The selection of foundational elements, the outlining of the system, and the final weighing are all collaborative activities and entail making decisions together by exchanging personal perspectives. As intended, also the *mission end* cards successfully accomplished this result, encouraging a retrospective discussion on the designed system and the whole experience.

4 Conclusions and future work

As Manzini stated in (Frascara, 2020), designers can operate in a variety of fields, and they can contribute to conceive and realize varied artifacts. A reason for this may be that "designers bring multiple talents to the solutions of complex issues, but first and foremost [...] empathy" (Friedman et al., 2014).

Empathy allows designers to understand the needs of all the people involved in a project, which implies absorbing their perspective. This is why, if properly equipped, they can comfortably navigate among disciplines and build upon their knowledge and methods, as corroborated by the empirical experiment above depicted. If the translation of technical knowledge (the primary objective of the activity) can be a delicate practice as it requires finding the correct language to efficaciously engage and empower designers to comprehend and make use of the transferred contents, instilling a value-sensitive perspective (secondary goal) appeared a far more natural outcome.

Indeed, going back to Alain Findeli's study on Ethics, Aesthetics, and Design (1994), he already stated that ethics is an expansion of the currently accepted design definition. He sustained that "ethical deliberation is not very different from any other decision-making process," suggesting that designers not only have the means and the capabilities to handle ethical questions, but they also inevitably act in the field of ethics when they design an artifact. In fact, like any human activity, design is not neutral:

choosing a technological mediation (in the broadest sense of creating instruments for people to interact with the world) is itself a matter of ethics, not of technology. Further assonances can be reported in that designers' criteria of choice do not arise from the truth (as in science), but from more qualitative evaluations of appropriateness, acceptability, correctness or desirability, and the now common practice of involving different stakeholders in the design process, that the author defines a "multicriteria approach," is already a moral action. What distinguishes a design decision from an ethical one is, in the words of Findeli (1994), a "total moral engagement on the actor's part," which, in line with the opening of this paragraph, can be reframed as the empathy representing a major strength of designers. To support once again the innate capability of designers to include ethical principles in their reasoning, Findeli (1994) underlines that "the systemic apprehension of a complex reality comes from intuition," a skill that designers have to train with appropriate methods but that is rooted in their previous education and practice.

After all, just as design pervades every aspect of human life, any field can be embraced and shaped by design, reinforcing the idea of a transdisciplinary design (Blevis et al., 2015) that transcends disciplinary boundaries. Expanding the frontiers of design, then, could contribute to the creation of a new kind of skill: that of mediating among approaches and value systems of a variety of disciplines (Kirschener & Norman, 2021). As self-conscious bricoleurs (Louridas, 1999), designers will not just merge the materials at hand; they could also identify and bring together different kinds of professionals to foster collaboration across multiple disciplines.

In the end, extending the breadth of design borders will not threaten a loss of identity. As demonstrated by the portrayed didactic experience, what characterizes designers is their attitude, their approach, and the processes they are used to apply to frame and solve problems. From its origins, design was outlined through the distinctive traits of other disciplines combined – namely, art, science, and technology. Today, this disciplinary distinction should be blurred and enclosed within a more general model to define a designer, whose essential skills would be perception (including visual intelligence) and (moral) action (Findeli, 2001). With such foundational equipment, the designer could easily merge into different disciplinary realms to deal with the most pressing problems and act as a bonding agent.

To support this vision, it would be interesting to expand the proposed introductory activity. It may be the building block for a more comprehensive educational project or include more vertical topics and become modular and flexible. Likewise, its finality could also be broadened, and further relevant insights could be gained from the submission of the game to students with different but inherent backgrounds. In the current state, if ethicists may not find cues to operationalize their knowledge, ML students could be interesting testers. Could a different perspective on *ML agents* enrich them? Can they get to design a system with the provided materials? How would they react to ethical concerns? Responding to this sort of questions may convey a deeper understanding of computer scientists or engineers' approach to the same problem, eventually suggesting how to facilitate communication with designers and make this game a basic tool for interdisciplinary problem-based teams (Friedman et al., 2019).

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